Thống kê máy tính và Ứng dụng
Học kì II, 2020 - 2021

ĐỒ ÁN 1

Sử dụng Hidden Markov Model

trong dự đoán giá chứng khoán

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Cơ sở lý thuyết

Có thể chuyển dữ liệu chứng khoán thu thập được về dạng

$$O_t = (\frac{close - open}{open}, \frac{high - open}{open}, \frac{open - low}{open}) \\ = (fracChange, fracHigh, fracLow)$$

với close là giá đóng cửa, open là giá mở cửa, high là giá cao nhất và low là giá thấp nhất của phiên giao dịch

Toàn bộ các điểm quan sát được trong dữ liệu huấn luyện sẽ được chuyển về dạng này để huấn luyện cho HMM

Áp dụng Maximum A Posterior (MAP) và cửa sổ trượt (Sliding window) d ngày, bài toán trở thành:

- Có HMM λ và các quan sát d ngày $(O_1, O_2, \dots, O_d)$ cùng với giá mở cửa (open) của ngày d+1, ta cần dự đoán giá đóng cửa (close) của ngày d+1.
- Bài toán tương đương với 'ước tính giá trị $fracChange = \frac{close-open}{open}$ cho ngày d+1'. Khi có được ước tính của fracChange, ta có thể ước tính giá đóng cửa: $close = open(1 + fracChange)$
- Vậy việc cần làm là ước tính MAP của O_{d+1}

Đặt $\hat{O}_{d+1}$ là ước tính MAP vào ngày d+1, có dữ liệu của d ngày trước đó, thì:

$$\hat{O}_{d+1} = \underset{O_{d+1}}{\operatorname{argmax}} P(O_{d+1}|O_1, O_2, \dots O_d, \lambda) \\ = \underset{O_{d+1}}{\operatorname{argmax}} \frac{P(O_1, O_2, \dots O_d, O_{d+1}|\lambda)}{P(O_1, O_2, \dots O_d, \lambda)} \\ = \underset{O_{d+1}}{\operatorname{argmax}} P(O_1, O_2, \dots O_d, O_{d+1}|\lambda)$$

Xác suất hợp (joint probability) $P(O_1, O_2, \dots O_d, O_{d+1}|\lambda)$ có thể được tính bằng sử dụng forward-backward algorithm của HMM. Sử dụng phương pháp này, tính xác suất của một tổ hợp các giá trị rời rạc của O_{d+1} và chọn giá trị có xác suất cực đại làm ước tính $\hat{O}_{d+1}$, từ đó dự đoán được giá đóng cửa của ngày d+1

Các thư viện hỗ trợ

In [1]:
```python
import datetime
from datetime import date
import pandas as pd

import time

%matplotlib inline
import matplotlib.pyplot as plt
plt.style.use('seaborn')
import statsmodels.api as sm
import os.path
import numpy as np
import math

from sklearn.model_selection import train_test_split
import pickle

from sklearn import set_config
set_config(display='diagram')

import gc

from IPython.display import display, HTML, clear_output

import yfinance as yf
from pandas_datareader import data as pdr

yf.pdr_override()

from copy import copy
import os
import pickle

from sklearn.preprocessing import StandardScaler

from financial_features import *

from hmmlearn.hmm import GaussianHMM

from sklearn.model_selection import train_test_split

import itertools

from progressbar import Percentage, ProgressBar,Bar,ETA

from sklearn.metrics import mean_absolute_percentage_error as mape, mean_absolute_error as mae

const_time_col = 'Date'
const_target_col = 'Close'
const_name_col = 'Name'
```

1. Thu thập dữ liệu

Sử dụng Yahoo API

Dữ liệu thu thập là dữ liệu từ 01/01/2005 đến 30/05/2021 của 3 loại cổ phiếu Google (GOOGL), Apple (AAPL), Gamestop (GME)

In [2]:
```python
def read_data(path, date_format='%Y-%m-%d'):
    all_stocks = pd.read_csv(path)
    all_stocks[const_time_col] = pd.to_datetime(all_stocks[const_time_col], format=date_format, errors='ignore'
    all_stocks = all_stocks.dropna(axis=0)
    all_stocks = all_stocks.set_index(const_time_col, drop=False)
    return all_stocks


def get_sp500_curr_stock_symbols():
    source = pd.read_html('https://en.wikipedia.org/wiki/List_of_S%26P_500_companies')
    stock_df = source[0]
    return stock_df['Symbol'].to_list()


def save_stock_pulled(file_name, ticket_lists, start_date, end_date, interval='1d'):
    """
    The requested range [start_day, end_date] must be within:
        - the last 730 days for '1h' interval.
        - the last 60 days for '90m' interval
    """
    final_df = pd.DataFrame()
    attr_list = ['Open', 'High', 'Low', 'Close', 'Volume']

    for ticket in ticket_lists:
        df_ = pdr.get_data_yahoo(ticket, start=start_date, end=end_date, interval=interval)[attr_list]
        df_['Name'] = ticket
        final_df = pd.concat([final_df, df_])

    final_df.index = pd.to_datetime(final_df.index).strftime('%Y/%m/%dT%H:%M:%S')
    final_df.to_csv(file_name + '.csv', index_label='Date')
    return
```

In [3]:
```python
#sp500 = get_sp500_curr_stock_symbols()
symbols = ['GOOGL', 'AAPL', 'GME']
#save_stock_pulled('stock_data', symbols, '2005-01-01', '2021-05-30')
```

2. Tiền xử lí

In [4]:
```python
def cal_features(data, norm_func=None, next_t=1, re_fit=True):
    feature_df = data[[const_target_col, 'Open']].copy()

    numeric_cols = data.select_dtypes(
        include=['int16', 'int32', 'int64', 'float16', 'float32', 'float64']).columns.tolist()

    feature_df['Close_proc'] = PROC(data['Close'], next_t) # Luôn giữ
    feature_df['frac_change'] = (data['Close'] - data['Open'])/data['Open']
    feature_df['frac_high'] = (data['High'] - data['Open'])/data['Open']
    feature_df['frac_low'] = (data['Open'] - data['Low'])/data['Open']

    return feature_df
```

3. Mô hình hóa

3.1. Đọc và xử lí dữ liệu

In [5]:
```python
data = read_data('stock_data.csv', date_format='%Y-%m-%d')

googl, apple, gamestop = 'GOOGL', 'AAPL', 'GME'

stock_df = data[data[const_name_col] == googl]
stock_df.head()
```

Out[5]:

	Date	Open	High	Low	Close	Volume	Name
Date							
2004-12-31	2004-12-31	99.714714	100.040039	96.376373	96.491493	15321663	GOOGL
2005-01-03	2005-01-03	98.798798	101.921921	97.827827	101.456459	31656712	GOOGL
2005-01-04	2005-01-04	100.800804	101.566566	96.836838	97.347343	27484288	GOOGL
2005-01-05	2005-01-05	96.821823	98.548546	96.211212	96.851852	16456727	GOOGL
2005-01-06	2005-01-06	97.637634	98.048050	93.953957	94.369370	20753426	GOOGL

In [6]:
```python
processed_df = cal_features(stock_df, norm_func=StandardScaler(), next_t=1, re_fit=True)
processed_df.head()
```

Out[6]:

	Close	Open	Close_proc	frac_change	frac_high	frac_low
Date						
2004-12-31	96.491493	99.714714	0.000000	-0.032324	0.003263	0.033479
2005-01-03	101.456459	98.798798	0.051455	0.026900	0.031611	0.009828
2005-01-04	97.347343	100.800804	-0.040501	-0.034260	0.007597	0.039325
2005-01-05	96.851852	96.821823	-0.005090	0.000310	0.017834	0.006307
2005-01-06	94.369370	97.637634	-0.025632	-0.033473	0.004203	0.037728

Tách dữ liệu thành dữ liệu huấn luyện (training data) và thử nghiệm (testing data)

In [7]:
```python
train_data, test_data = train_test_split(processed_df, test_size=0.15, shuffle=False)
```

In [8]:
```python
train_data.head()
```

Out[8]:

	Close	Open	Close_proc	frac_change	frac_high	frac_low
Date						
2004-12-31	96.491493	99.714714	0.000000	-0.032324	0.003263	0.033479
2005-01-03	101.456459	98.798798	0.051455	0.026900	0.031611	0.009828
2005-01-04	97.347343	100.800804	-0.040501	-0.034260	0.007597	0.039325
2005-01-05	96.851852	96.821823	-0.005090	0.000310	0.017834	0.006307
2005-01-06	94.369370	97.637634	-0.025632	-0.033473	0.004203	0.037728

In [9]:
```python
train_data.shape
```

Out[9]:
```
(3511, 6)
```

In [10]:
```python
test_data.head()
```

Out[10]:

	Close	Open	Close_proc	frac_change	frac_high	frac_low
Date						
2018-12-12	1073.729980	1077.079956	0.011378	-0.003110	0.013602	0.004744
2018-12-13	1073.540039	1075.670044	-0.000177	-0.001980	0.011853	0.009929
2018-12-14	1051.709961	1060.020020	-0.020335	-0.007840	0.011037	0.010047
2018-12-17	1025.650024	1047.010010	-0.024779	-0.020401	0.014680	0.029016
2018-12-18	1043.410034	1034.000000	0.017316	0.009101	0.024845	0.003404

In [11]:
```python
test_data.shape
```

Out[11]:
```
(620, 6)
```

3.2. Cài đặt mô hình HMM

In [12]:
```python
def create_ft_vector(df, ft):
    col = [df[c] for c in ft]
    return np.column_stack(col)
```

Mô hình sử dụng vector thuộc tính

$$O_t = (\frac{close - open}{open}, \frac{high - open}{open}, \frac{open - low}{open}) \\ = (fracChange, fracHigh, fracLow)$$

In [13]:
```python
class Open_HMM_Model:
    def __init__(self, n_components):
        self.frac_change_min, self.frac_change_max = None, None
        self.frac_high_min, self.frac_high_max = None, None
        self.frac_low_min, self.frac_low_max = None, None
        self.hmm = GaussianHMM(n_components=n_components)

    def fit(self, train_data=None):
        ft_vector = create_ft_vector(train, ['frac_change', 'frac_high', 'frac_low'])
        self.hmm.fit(ft_vector)

        self.frac_change_min, self.frac_change_max = min(train['frac_change']), max(train['frac_change'])
        self.frac_high_min, self.frac_high_max = min(train['frac_high']), max(train['frac_high'])
        self.frac_low_min, self.frac_low_max = min(train['frac_low']), max(train['frac_low'])

    def compute_all_possible_outcomes(self, n_steps_frac_change, n_steps_frac_high, n_steps_frac_low):
        frac_change_range = np.linspace(self.frac_change_min, self.frac_change_max, n_steps_frac_change)
        frac_high_range = np.linspace(self.frac_high_min, self.frac_high_max, n_steps_frac_high)
        frac_low_range = np.linspace(self.frac_low_min, self.frac_low_max, n_steps_frac_low)

        return np.array(list(itertools.product(frac_change_range, frac_high_range, frac_low_range)))

    def predict_day(self, dataset, day_index,  w_len):
        previous_data = dataset.iloc[max(0, day_index - w_len): max(0, day_index - 1)]
        previous_data_features = create_ft_vector(previous_data, ['frac_change', 'frac_high', 'frac_low'])

        outcome_score = []
        possible_outcomes = self.compute_all_possible_outcomes(50, 10, 10)

        for possible_outcome in possible_outcomes:
            total_data = np.row_stack((previous_data_features, possible_outcome))
            outcome_score.append(self.hmm.score(total_data))

        most_probable_outcome = possible_outcomes[np.argmax(outcome_score)]

        open_price = dataset.iloc[day_index]['Open']
        predicted_frac_change = most_probable_outcome[0]

        return open_price * (1 + predicted_frac_change)

    def predict(self, dataset, w_len):
        pbar = ProgressBar(widgets=[Bar('=', '[', ']'), ' ', Percentage(), ' ', ETA()],
                   maxval=100).start()

        pred_close = []
        for i in pbar(range(w_len, dataset.shape[0])):
            pred_close.append(self.predict_day(dataset, i, w_len))
        return pred_close
```

Mô hình sử dụng vector thuộc tính

$$O_t = (\frac{close - \text{last\_close}}{\text{last\_close}}) \\ = (closePROC) \ (\text{PROC} = \text{Price rate of change})$$

In [14]:
```python
class LastClose_HMM_Model:
    def __init__(self, n_components):
        self.proc_min, self.proc_max = None, None
        self.hmm = GaussianHMM(n_components=n_components)


    def fit(self, train_data=None):
        ft_vector = create_ft_vector(train, ['Close_proc'])
        self.hmm.fit(ft_vector)

        self.proc_min, self.proc_max = min(train['Close_proc']), max(train['Close_proc'])

    def compute_all_possible_outcomes(self, n_steps):
        return np.linspace(self.proc_min, self.proc_max, n_steps)

    def predict_day(self, dataset, day_index,  w_len):
        previous_data = dataset.iloc[max(0, day_index - w_len): max(0, day_index - 1)]
        previous_data_features = create_ft_vector(previous_data, ['Close_proc'])

        outcome_score = []
        possible_outcomes = self.compute_all_possible_outcomes(5000)

        for possible_outcome in possible_outcomes:
            total_data = np.row_stack((previous_data_features, possible_outcome))
            outcome_score.append(self.hmm.score(total_data))

        most_probable_outcome = possible_outcomes[np.argmax(outcome_score)]

        last_price = dataset.iloc[day_index-1]['Close']
        predicted_frac_change = most_probable_outcome

        return last_price * (1 + predicted_frac_change)

    def predict(self, dataset, w_len):
        pbar = ProgressBar(widgets=[Bar('=', '[', ']'), ' ', Percentage(), ' ', ETA()],
                   maxval=100).start()

        pred_close = []
        for i in pbar(range(w_len, dataset.shape[0])):
            pred_close.append(self.predict_day(dataset, i, w_len))
        return pred_close
```

In [15]:
```python
def run_test(trainset, valset, n_hidden_states, w_len):
    model1 = Open_HMM_Model(n_components = n_hidden_states)
    model1.fit(trainset)

    model2 = LastClose_HMM_Model(n_components = n_hidden_states)
    model2.fit(trainset)

    pred1 = model1.predict(valset, w_len)
    pred2 = model2.predict(valset, w_len)

    df = pd.DataFrame(list(zip(valset['Close'][w_len:], pred1, pred2)), \
                columns =['True val', 'Pred 1', 'Pred 2'], index=valset[w_len:].index)

    return df, mape(df['True val'], df['Pred 1'])*100, mae(df['True val'], df['Pred 1']), \
           mape(df['True val'], df['Pred 2'])*100, mae(df['True val'], df['Pred 2'])
```

In [16]:
```python
def run_multi_test(trainset, valset, l_hidden_states, l_w_len, saved_result_to):
    mape1, mape2, mae1, mae2 = [], [], [], []
    config = []

    if not os.path.isfile(saved_result_to):
        with open(eval_result_path, "w") as file:
            file.write("Config, MAPE 1, MAE 1, MAPE 2, MAE 2\n")
            file.close()

    for n_hidden_states in l_hidden_states:
        print(' - No. of hidden states:', n_hidden_states)
        for w_len in l_w_len:
            print('   + Window length:', w_len)
            _df, mp1, m1, mp2, m2 = run_test(trainset, valset, n_hidden_states, w_len)

            with open(saved_result_to, "a") as file:
                file.write("{0}, {1}, {2}, {3}, {4}\n".format((n_hidden_states, w_len), mp1, m1, mp2, m2))
                file.close()

            config.append((n_hidden_states, w_len))
            mape1.append(mp1)
            mae1.append(m1)
            mape2.append(mp2)
            mae2.append(m2)

    result = pd.DataFrame(list(zip(config, mape1, mae1, mape2, mae2)), \
                columns =['Config', 'MAPE 1', 'MAE 1', 'MAPE 2', 'MAE 2'])

    return result
```

3.3. Tìm mô hình tốt nhất

In [17]:
```python
train, validation = train_test_split(train_data, test_size=0.2, shuffle=False)
```

In [18]:
```python
result_df = run_multi_test(train, validation, [4, 5, 6, 7], [10, 20, 30 , 40], 'googl_result.csv')
```

```
 - No. of hidden states: 4
   + Window length: 10
[==========================================================] 100% Time: 0:20:19
[==========================================================] 100% Time: 0:20:48
   + Window length: 20
[==========================================================] 100% Time: 0:21:44
[==========================================================] 100% Time: 0:19:52
   + Window length: 30
[==========================================================] 100% Time: 0:20:00
[==========================================================] 100% Time: 0:19:28
   + Window length: 40
[==========================================================] 100% Time: 0:19:48
[==========================================================] 100% Time: 0:19:24
 - No. of hidden states: 5
   + Window length: 10
[==========================================================] 100% Time: 0:17:33
[==========================================================] 100% Time: 0:15:49
   + Window length: 20
[==========================================================] 100% Time: 0:16:26
[==========================================================] 100% Time: 0:18:00
   + Window length: 30
[==========================================================] 100% Time: 0:18:16
[==========================================================] 100% Time: 0:15:58
   + Window length: 40
[==========================================================] 100% Time: 0:16:15
[==========================================================] 100% Time: 0:15:48
 - No. of hidden states: 6
   + Window length: 10
[==========================================================] 100% Time: 0:19:23
[==========================================================] 100% Time: 0:20:20
   + Window length: 20
[==========================================================] 100% Time: 0:22:02
[==========================================================] 100% Time: 0:21:49
   + Window length: 30
[==========================================================] 100% Time: 0:21:36
[==========================================================] 100% Time: 0:21:07
   + Window length: 40
[==========================================================] 100% Time: 0:21:08
[==========================================================] 100% Time: 0:16:38
 - No. of hidden states: 7
   + Window length: 10
[==========================================================] 100% Time: 0:19:29
[==========================================================] 100% Time: 0:19:17
   + Window length: 20
[==========================================================] 100% Time: 0:21:08
[==========================================================] 100% Time: 0:21:17
   + Window length: 30
[==========================================================] 100% Time: 0:18:53
[==========================================================] 100% Time: 0:16:21
   + Window length: 40
[==========================================================] 100% Time: 0:17:04
[==========================================================] 100% Time: 0:16:24
```

In [20]:
```python
result_df
```

Out[20]:

	Config	MAPE 1	MAE 1	MAPE 2	MAE 2
0	(4, 10)	1.088707	10.572805	0.927528	9.079502
1	(4, 20)	1.089990	10.616777	0.934645	9.163568
2	(4, 30)	1.092720	10.671305	0.936802	9.210053
3	(4, 40)	1.093500	10.711201	0.932767	9.211638
4	(5, 10)	0.855315	8.418909	0.927546	9.080700
5	(5, 20)	0.863728	8.529782	0.934748	9.165428
6	(5, 30)	0.863423	8.554048	0.937024	9.212887
7	(5, 40)	0.858348	8.531092	0.932789	9.212877
8	(6, 10)	0.862603	8.456136	0.927563	9.080962
9	(6, 20)	0.867270	8.516513	0.934749	9.165454
10	(6, 30)	0.873216	8.620179	0.937040	9.213106
11	(6, 40)	0.868524	8.586271	0.932799	9.212986
12	(7, 10)	0.868120	8.506427	0.927581	9.080985
13	(7, 20)	0.873126	8.574490	0.934741	9.165248
14	(7, 30)	0.871658	8.591633	0.937023	9.212852
15	(7, 40)	0.872690	8.621314	0.932844	9.213331

In [24]:
```python
result_df.loc[result_df['MAPE 1'].argmin()]
```

Out[24]:
```
Config     (5, 10)
MAPE 1    0.855315
MAE 1     8.418909
MAPE 2    0.927546
MAE 2       9.0807
Name: 4, dtype: object
```

In [25]:
```python
result_df.loc[result_df['MAE 1'].argmin()]
```

Out[25]:
```
Config     (5, 10)
MAPE 1    0.855315
MAE 1     8.418909
MAPE 2    0.927546
MAE 2       9.0807
Name: 4, dtype: object
```

In [26]:
```python
result_df.loc[result_df['MAPE 2'].argmin()]
```

Out[26]:
```
Config      (4, 10)
MAPE 1     1.088707
MAE 1     10.572805
MAPE 2     0.927528
MAE 2      9.079502
Name: 0, dtype: object
```

In [27]:
```python
result_df.loc[result_df['MAE 2'].argmin()]
```

Out[27]:
```
Config      (4, 10)
MAPE 1     1.088707
MAE 1     10.572805
MAPE 2     0.927528
MAE 2      9.079502
Name: 0, dtype: object
```

4. Đánh giá mô hình

4.1. Huấn luyện 2 mô hình tốt nhất trên toàn bộ tập huấn luyện

In [28]:
```python
model1 = Open_HMM_Model(n_components = 5)
model1.fit(train_data)
pred1 = model1.predict(test_data, w_len = 10)
```

```
[==========================================================] 100% Time: 0:14:30
```

In [29]:
```python
model2 = LastClose_HMM_Model(n_components = 4)
model2.fit(train_data)
pred2 = model2.predict(test_data, w_len = 10)
```

```
[==========================================================] 100% Time: 0:14:16
```

In [30]:
```python
df = pd.DataFrame(list(zip(test_data['Close'][10:], pred1, pred2)), \
                columns =['Actual price', 'Predicted 1', 'Predicted 2'], index=test_data[10:].index)
df.head()
```

Out[30]:

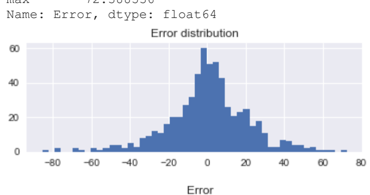
	Actual price	Predicted 1	Predicted 2
Date			
2018-12-27	1052.900024	1022.166428	1049.076650
2018-12-28	1046.680054	1047.577662	1053.932936
2018-12-31	1044.959961	1045.926411	1047.905358
2019-01-02	1054.680054	1038.205334	1046.183252
2019-01-03	1025.469971	1061.926885	1055.914723

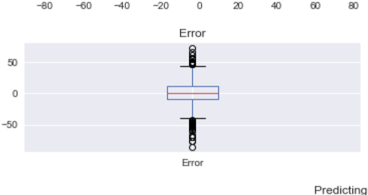
4.2. Độ lỗi mô hình

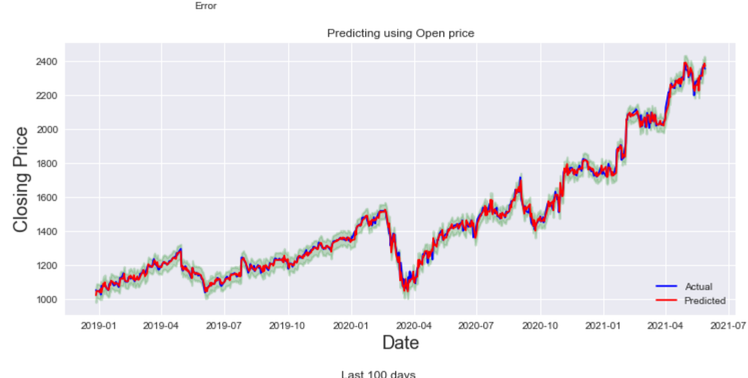
In [31]:
```python
def plot_model_prediction(Y, predicted_Y, idx, title='', eval_error=False, zoom_in=[], zoom_title=''):
    valid_vs_prediction = pd.DataFrame({'Actual': Y}, index=idx)
    valid_vs_prediction['Predicted'] = predicted_Y
    valid_vs_prediction['Error'] = valid_vs_prediction['Actual'] - valid_vs_prediction['Predicted']


    std_part = 1.96 # Độ tin cậy 95%, [11]
    err_std = valid_vs_prediction['Error'].std(axis=0)
    err_mean = np.absolute(valid_vs_prediction['Error'].mean(axis=0))

    pred_upper = valid_vs_prediction['Predicted'] + err_mean + err_std * std_part
    pred_lower = valid_vs_prediction['Predicted'] - err_mean - err_std * std_part

    if eval_error:
        print('Comparing metric:')
        print(' - MAPE:', mape(valid_vs_prediction['Actual'], valid_vs_prediction['Predicted'])*100, '%')
        print(' - MAE:', mae(valid_vs_prediction['Actual'], valid_vs_prediction['Predicted']))
        print('Error.describe:')
        print(valid_vs_prediction['Error'].describe())
        plt.figure(figsize=(6,2))
        valid_vs_prediction['Error'].hist(bins=50).set_title('Error distribution')
        plt.show()
        plt.figure(figsize=(6,2))
        valid_vs_prediction['Error'].plot(kind='box', grid=True).set_title("Error")
        plt.show()

    plt.figure(figsize=(12,5))
    plt.title(title)
    plt.xlabel('Date', fontsize=18)
    plt.ylabel('Closing Price', fontsize=18)
    plt.plot(valid_vs_prediction['Actual'], color='b')
    plt.plot(valid_vs_prediction['Predicted'], color='r')
    plt.fill_between(x=valid_vs_prediction.index, y1=pred_upper, y2=pred_lower,
                     color='green', lw=2, alpha=0.2)
    plt.legend(['Actual', 'Predicted'], loc='lower right')
    plt.show()

    if len(zoom_in) > 0:
        plt.figure(figsize=(12,6))
        plt.title(zoom_title)
        plt.plot(valid_vs_prediction['Actual'][zoom_in[0]:zoom_in[1]],
                 label='Actual', marker='o', color='b')
        plt.plot(valid_vs_prediction['Predicted'][zoom_in[0]:zoom_in[1]],
                 label='Predicted', marker='o', color='r')
        plt.fill_between(x=valid_vs_prediction.index[zoom_in[0]:zoom_in[1]],
                         y1=pred_upper[zoom_in[0]:zoom_in[1]],
                         y2=pred_lower[zoom_in[0]:zoom_in[1]], color='green', lw=2, alpha=0.2)
        plt.legend(loc='lower right')
        plt.show()
```

In [32]:
```python
plot_model_prediction(df['Actual price'], df['Predicted 1'], idx=df.index,
                      title = 'Predicting using Open price', eval_error=True,
                      zoom_in=[-100,None], zoom_title='Last 100 days')
```

```
Comparing metric:
 - MAPE: 1.0601272958077812 %
 - MAE: 15.401251831504666
Error.describe:
count     610.000000
mean        0.667944
std        21.242205
min       -85.439112
25%        -9.510531
50%         0.773668
75%        11.895790
max        72.388536
Name: Error, dtype: float64
```

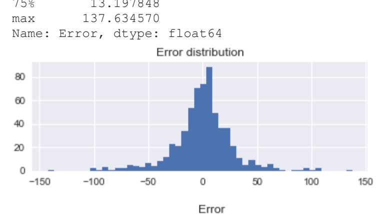


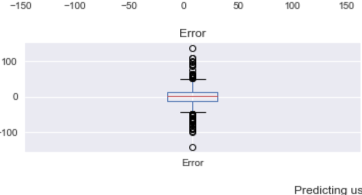


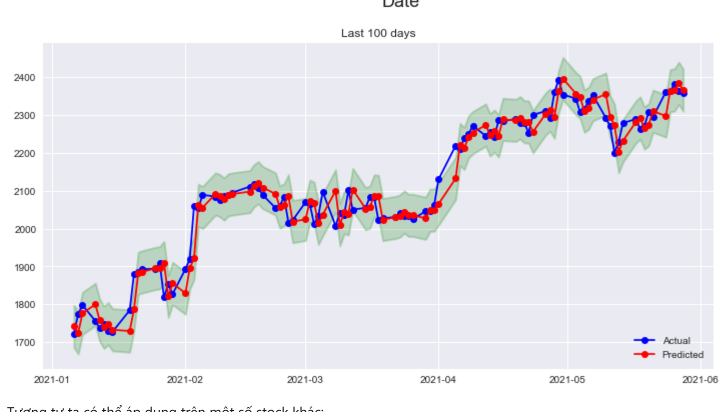


In [42]:
```python
plot_model_prediction(df['Actual price'], df['Predicted 2'], idx=df.index,
                      title = 'Predicting using Last Close price', eval_error=True,
                      zoom_in=[-100,None], zoom_title='Last 100 days')
```

```
Comparing metric:
 - MAPE: 1.3246458112894877 %
 - MAE: 19.096077225971356
Error.describe:
count     610.000000
mean        0.452033
std        28.237203
min      -142.384479
25%       -11.181931
50%         0.583478
75%        13.197848
max       137.634570
Name: Error, dtype: float64
```







Tương tự ta có thể áp dụng trên một số stock khác:

- AAPL

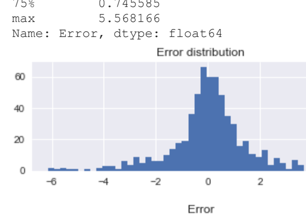
In [34]:
```python
apple_df = data[data[const_name_col] == 'AAPL']
apple_processed_df = cal_features(apple_df, norm_func=StandardScaler(), next_t=1, re_fit=True)
apple_train_data, apple_test_data = train_test_split(apple_processed_df, test_size=0.15, shuffle=False)
```

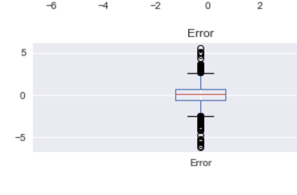
In [35]:
```python
apple_model1 = Open_HMM_Model(n_components = 5)
apple_model1.fit(apple_train_data)
apple_pred1 = apple_model1.predict(apple_test_data, w_len = 10)

apple_model2 = LastClose_HMM_Model(n_components = 4)
apple_model2.fit(apple_train_data)
apple_pred2 = apple_model2.predict(apple_test_data, w_len = 10)

apple_df = pd.DataFrame(list(zip(apple_test_data['Close'][10:], apple_pred1, apple_pred2)), \
                columns =['Actual price', 'Predicted 1', 'Predicted 2'], index=apple_test_data[10:].index)
```

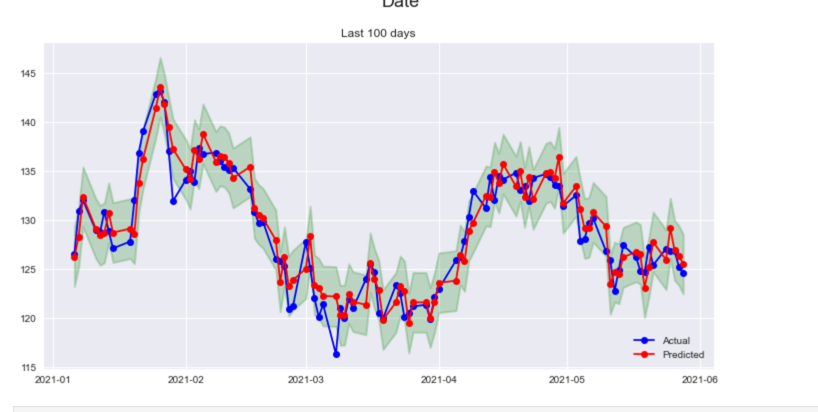
```
[==========================================================] 100% Time: 0:14:26
[==========================================================] 100% Time: 0:14:29
```

In [36]:
```python
plot_model_prediction(apple_df['Actual price'], apple_df['Predicted 1'], idx=apple_df.index,
                      title = 'Predicting using Open price', eval_error=True,
                      zoom_in=[-100,None], zoom_title='Last 100 days')
```

```
Comparing metric:
 - MAPE: 1.215848927004485 %
 - MAE: 1.0610153690122794
Error.describe:
count    610.000000
mean       0.020542
std        1.545341
min       -6.152933
25%       -0.562573
50%        0.063269
75%        0.745585
max        5.568166
Name: Error, dtype: float64
```

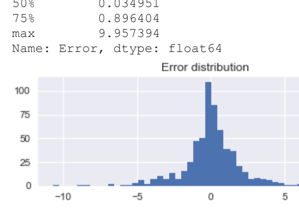


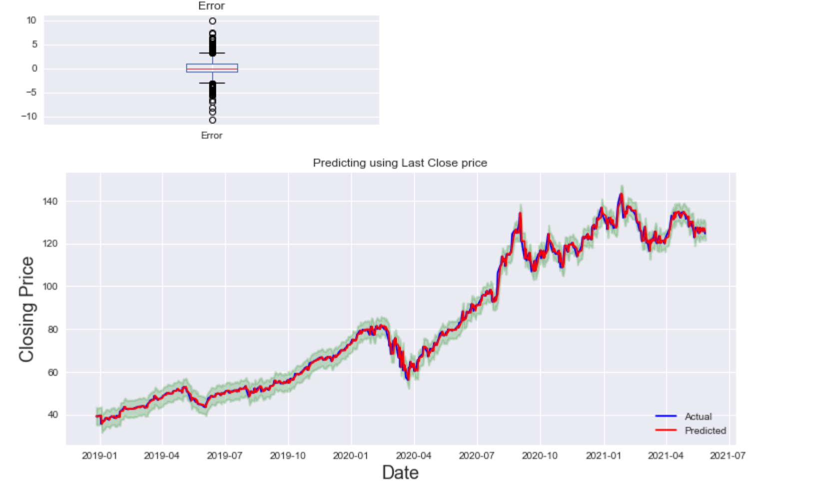


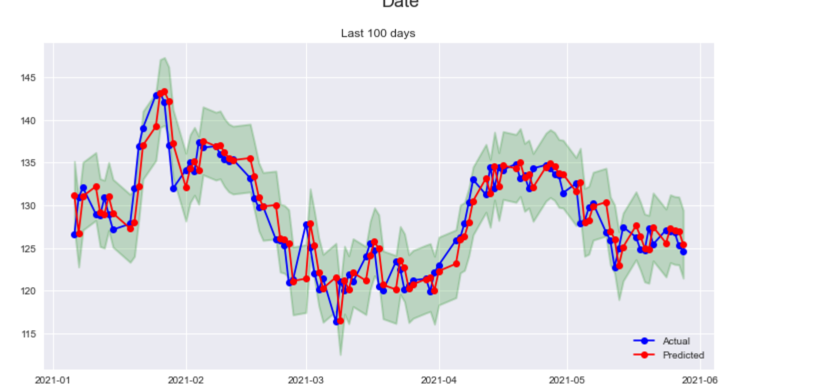


In [43]:
```python
plot_model_prediction(apple_df['Actual price'], apple_df['Predicted 2'], idx=apple_df.index,
                      title = 'Predicting using Last Close price', eval_error=True,
                      zoom_in=[-100,None], zoom_title='Last 100 days')
```

```
Comparing metric:
 - MAPE: 1.5716997053963517 %
 - MAE: 1.3281031026575085
Error.describe:
count    610.000000
mean       0.044313
std        2.005614
min      -10.665515
25%       -0.720697
50%        0.034951
75%        0.896404
max        9.957394
Name: Error, dtype: float64
```







- GME

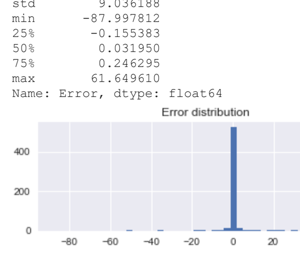
In [38]:
```python
gme_df = data[data[const_name_col] == 'GME']
gme_processed_df = cal_features(gme_df, norm_func=StandardScaler(), next_t=1, re_fit=True)
gme_train_data, gme_test_data = train_test_split(gme_processed_df, test_size=0.15, shuffle=False)
```

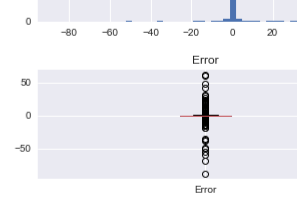
In [39]:
```python
gme_model1 = Open_HMM_Model(n_components = 5)
gme_model1.fit(gme_train_data)
gme_pred1 = apple_model1.predict(gme_test_data, w_len = 10)

gme_model2 = LastClose_HMM_Model(n_components = 4)
gme_model2.fit(gme_train_data)
gme_pred2 = apple_model2.predict(gme_test_data, w_len = 10)

gme_df = pd.DataFrame(list(zip(gme_test_data['Close'][10:], gme_pred1, gme_pred2)), \
                  columns =['Actual price', 'Predicted 1', 'Predicted 2'], index=apple_test_data[10:].index)
```

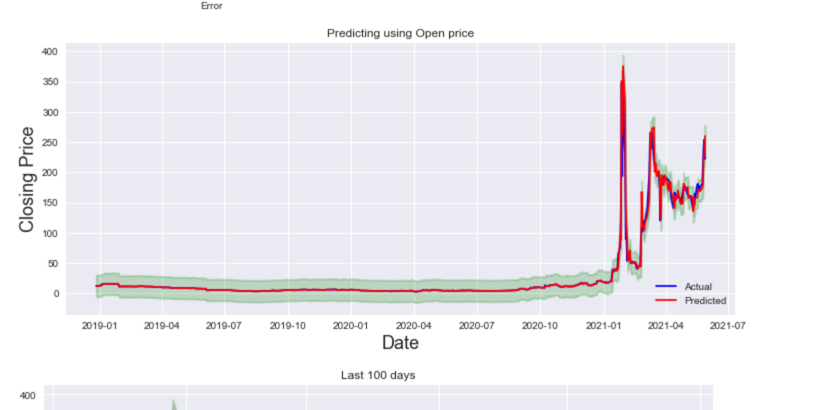
```
[==========================================================] 100% Time: 0:14:28
[==========================================================] 100% Time: 0:13:58
```

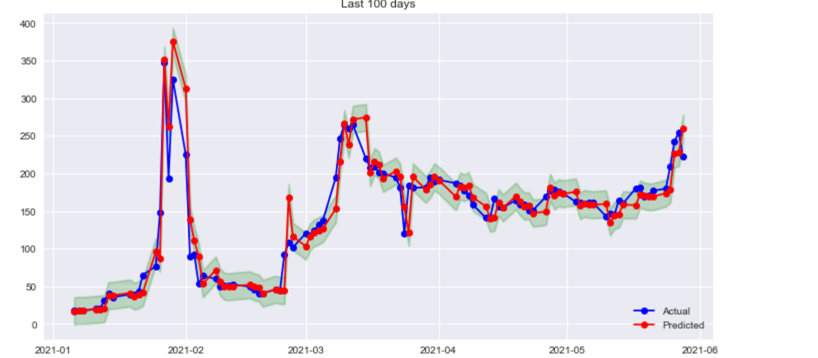
In [40]:
```python
plot_model_prediction(gme_df['Actual price'], gme_df['Predicted 1'], idx=gme_df.index,
                      title = 'Predicting using Open price', eval_error=True,
                      zoom_in=[-100,None], zoom_title='Last 100 days')
```

```
Comparing metric:
 - MAPE: 4.58046213249318 %
 - MAE: 2.4516407040127763
Error.describe:
count    610.000000
mean      -0.115058
std        9.036188
min      -87.997812
25%       -0.155383
50%        0.031950
75%        0.246295
max       61.649610
Name: Error, dtype: float64
```



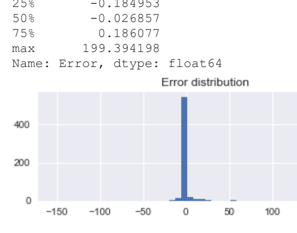


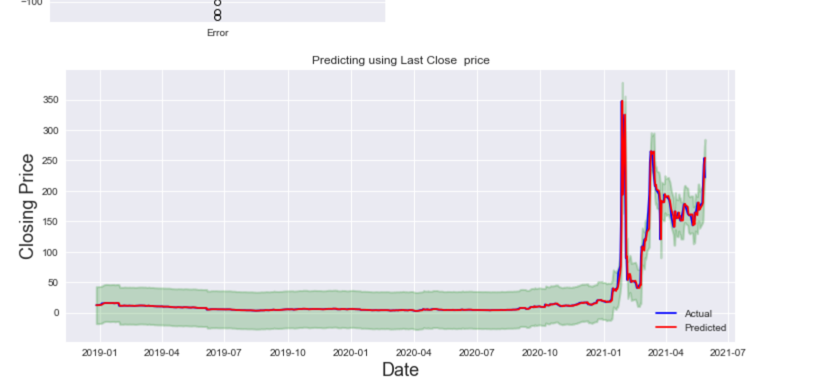


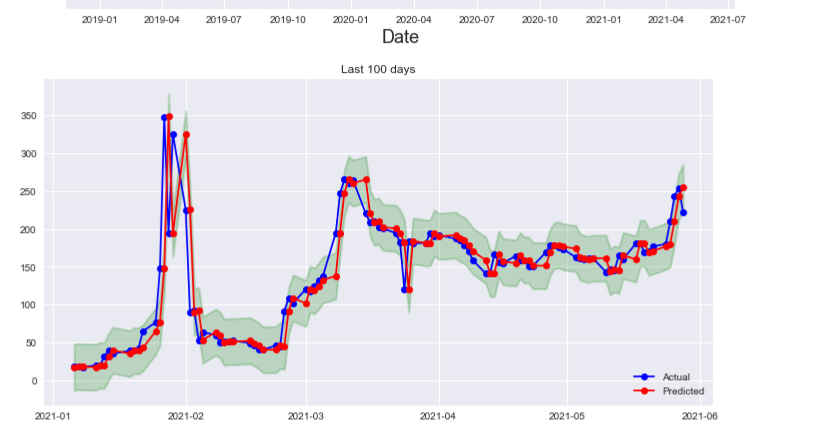


In [44]:
```python
plot_model_prediction(gme_df['Actual price'], gme_df['Predicted 2'], idx=gme_df.index,
                      title = 'Predicting using Last Close  price', eval_error=True,
                      zoom_in=[-100,None], zoom_title='Last 100 days')
```

```
Comparing metric:
 - MAPE: 5.361398404306387 %
 - MAE: 3.173499508870524
Error.describe:
count    610.000000
mean       0.313163
std       15.334848
min     -154.228949
25%       -0.184953
50%       -0.026857
75%        0.186077
max      199.394198
Name: Error, dtype: float64
```







5. Nguồn tham khảo

[1] https://insights.magestore.com/posts/giai-thuat-time-series-forecasting

[2] https://hmmlearn.readthedocs.io/en/latest/tutorial.html

[3] http://www.cs.cmu.edu/~bdhingra/papers/stock_hmm.pdf

In [ ]: