Machine Learning for Bitcoin Price Prediction and Sentiment Analysis

In this project I have two problems I want to solve, they are

1. I want to recognize patterns in BTC/USDT to forecast what will happen to the price in the next 12 hours with some technical indicators (Engineering features)
2. I want to get sentiment analysis from any source like CoinDesk or CryptoPanic

Let's focus on number one first, right now, we need bitcoin price data, it's more important than anything else, but wait... how can we get up-to-date data from the market? Ohh I know, previously I had a similar project like this and I used ccxt to get bitget data. Oke, lets get bitcoin data from bitget...

DISCLAIMER

Everything I do here is just for brain training and personal experimentation. Not everything should be trusted or used as a benchmark for investment or trading. The goal is just to learn and apply the Data Science knowledge that I have learned so far.

In [1]:
```
# pip install pycoingecko ccxt ta snscrape
```

In [2]:
```
import pandas as pd
import ccxt
```

Get Data from API

In [3]:
```
bitget = ccxt.bitget()
ohlcv = bitget.fetch_ohlcv('BTC/USDT', timeframe='1h', limit=1000)
```

EDA (Exploratory Data Analysis)

In [4]:
```
df = pd.DataFrame(ohlcv, columns=['timestamp', 'open', 'high', 'low', 'close', 'volume'])
df['timestamp'] = pd.to_datetime(df['timestamp'], unit='ms')
df.set_index('timestamp', inplace=True)

df
```

Out[4]:

timestamp	open	high	low	close	volume
2025-03-04 15:00:00	83216.68	83387.09	81520.90	82999.99	1002.587290
2025-03-04 16:00:00	82999.99	83790.00	82022.41	83552.68	1179.901143
2025-03-04 17:00:00	83552.68	85530.27	83429.00	85450.72	884.769535
2025-03-04 18:00:00	85450.72	86900.00	85173.18	86765.01	812.538519
2025-03-04 19:00:00	86765.01	88467.73	86535.02	88200.01	1195.767062
...	...	...	...	...	...
2025-04-15 02:00:00	84966.20	85284.50	84697.47	85220.32	296.418309
2025-04-15 03:00:00	85220.32	85403.63	85068.00	85365.43	345.552030
2025-04-15 04:00:00	85365.43	85511.68	85155.07	85485.87	314.500596
2025-04-15 05:00:00	85485.87	85855.86	85473.01	85535.48	373.851146
2025-04-15 06:00:00	85535.48	85678.00	85362.00	85400.22	217.607356

1000 rows × 5 columns

Right now we have the data, but we don't know if the data is good or there are actually zero values or missing values? But I'm pretty sure if the data is up-to-date from the market, we won't have zero/missing values, but let's check first

In [5]:
```
#Check Missing Values
df.info()
df.describe()
```

```
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1000 entries, 2025-03-04 15:00:00 to 2025-04-15 06:00:00
Data columns (total 5 columns):
 #   Column  Non-Null Count  Dtype  
---  ------  --------------  -----  
 0   open    1000 non-null   float64
 1   high    1000 non-null   float64
 2   low     1000 non-null   float64
 3   close   1000 non-null   float64
 4   volume  1000 non-null   float64
dtypes: float64(5)
memory usage: 46.9 KB
```

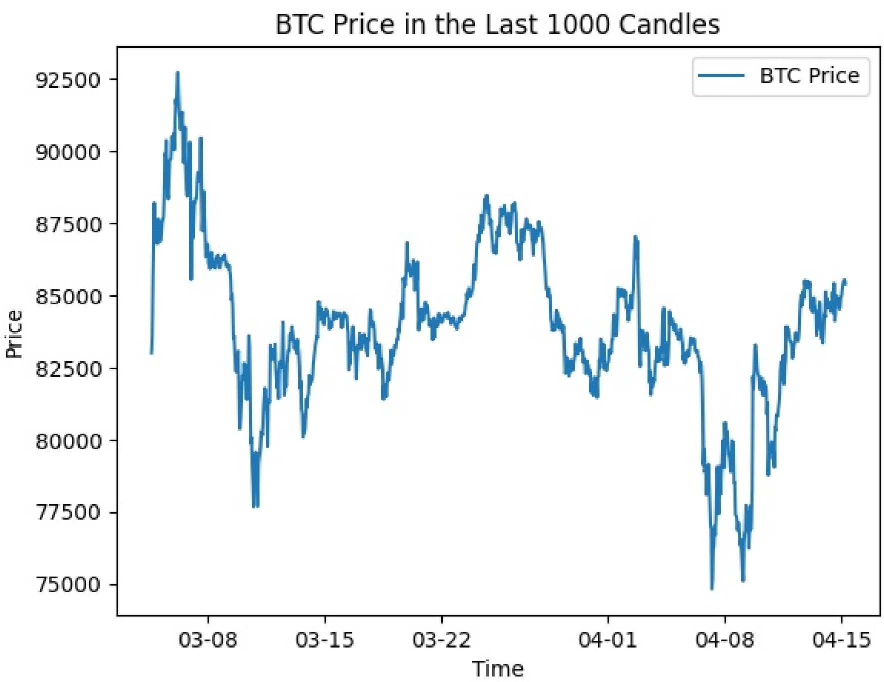
Out[5]:

	open	high	low	close	volume
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	83897.264280	84246.455350	83561.982620	83899.447820	375.060114
std	2808.649191	2784.765309	2849.135769	2808.968313	432.975775
min	74828.000000	75486.720000	74522.270000	74828.000000	24.073424
25%	82567.252500	82881.307500	82249.995000	82567.252500	149.520707
50%	83883.450000	84126.735000	83617.345000	83889.445000	244.524613
75%	85345.312500	85716.702500	85093.030000	85356.940000	433.774531
max	92728.210000	92794.110000	92135.000000	92728.210000	5328.027275

okay, thats good, we dont have missing values, lets see the price of bitcoin in the last 1000 candles

In [6]:
```
import matplotlib.pyplot as plt
import matplotlib.dates as mdates
```

In [7]:
```
#Check Linechar, i want to see the price of BTC in the last 1000 candles

plt.plot(df.index, df['close'], label='BTC Price')
plt.gca().xaxis.set_major_formatter(mdates.DateFormatter('%m-%d'))
plt.xlabel('Time')
plt.ylabel('Price')
plt.title('BTC Price in the Last 1000 Candles')
plt.legend()
plt.show()
```



Analyze Data

Previously we see the data and i think the data is healthy, we can up the stairs. In this part we will analyze the data, and we have to recognize what features make a good prediction. Actually, I don't have the experience to know what features make a good prediction. I am a trader and I know that the market is actually unpredictable and actually traders only use historical data to predict the future... and that's hard.

But, lets get the technical indicator first, i will use RSI, ATR, Bollinger Bands, Volatility, etc. (We will use ta library)

In [8]:

```python
import numpy as np
from ta.momentum import RSIIndicator
from ta.volatility import BollingerBands
from ta.volatility import AverageTrueRange

atr = AverageTrueRange(df['high'], df['low'], df['close'], window=14)
bb = BollingerBands(close=df['close'], window=20, window_dev=2)
```

In [9]:

```python
df_analyze = df.copy() # Copy data

df_analyze['close_future_6'] = df_analyze['close'].shift(6)
df_analyze['price_movement'] = (df_analyze['close_future_6'] > df_analyze['close']).astype(int)
df_analyze['close_future_1'] = df_analyze['close'].shift(3)
df_analyze['candle_body_pct'] = (df_analyze['close'] - df_analyze['open']) / (df_analyze['high'] - df_analyze['
df_analyze['volume_change'] = df_analyze['volume'].diff()
df_analyze['bb_width'] = bb.bollinger_hband() - bb.bollinger_lband()
df_analyze['close_pct_1'] = df_analyze['close'].pct_change(1)
df_analyze['return_lag_1'] = df_analyze['close_pct_1'].shift(1)
df_analyze['volatility_5'] = df_analyze['close_pct_1'].rolling(5).std()
df_analyze['ema_10'] = df_analyze['close'].ewm(span=10).mean()
df_analyze['ema_20'] = df_analyze['close'].ewm(span=20).mean()
df_analyze['ema_10_rel'] = df_analyze['close'] / df_analyze['close'].ewm(span=10).mean() - 1
df_analyze['ema_20_rel'] = df_analyze['close'] / df_analyze['close'].ewm(span=20).mean() - 1
df_analyze['ema_cross'] = ((df_analyze['ema_10'] > df_analyze['ema_20']) &
                          (df_analyze['ema_10'].shift(1) <= df_analyze['ema_20'].shift(1))).astype(int)
df_analyze['rsi'] = RSIIndicator(df_analyze['close'], window=14).rsi()
df_analyze['rsi_change'] = df_analyze['rsi'] - df_analyze['rsi'].shift(6)
df_analyze['bb_width_change'] = df_analyze['bb_width'].pct_change(3)
df_analyze['vol_accel'] = df_analyze['volume'].pct_change().pct_change()
df_analyze['returns'] = df_analyze['close'].pct_change() * 100
df_analyze['atr'] = atr.average_true_range()
df_analyze['wick_upper'] = df['high'] - df[['open', 'close']].max(axis=1)
df_analyze['wick_lower'] = df[['open', 'close']].min(axis=1) - df['low']
df_analyze['price_activity_ratio'] = (df_analyze['high'] - df_analyze['low']) / (df_analyze['high'].rolling(12)
df_analyze['volume_ratio_4h'] = df_analyze['volume'] / df_analyze['volume'].rolling(4).mean()
df_analyze['rsi_slope'] = df_analyze['rsi'] - df_analyze['rsi'].shift(3)
df_analyze['atr_change'] = df_analyze['atr'].pct_change(4)
df_analyze['close_momentum_6h'] = df_analyze['close'] / df_analyze['close'].shift(6) - 1
df_analyze['close_momentum_12h'] = df_analyze['close'] / df_analyze['close'].shift(12) - 1
df_analyze['close_momentum_24h'] = df_analyze['close'] / df_analyze['close'].shift(24) - 1
df_analyze['price_zscore'] = (df_analyze['close'] - df_analyze['close'].rolling(50).mean()) / df_analyze['close
df_analyze['hour'] = df_analyze.index.hour
df_analyze['hour_sin'] = np.sin(2 * np.pi * df_analyze.index.hour / 24)
df_analyze['hour_cos'] = np.cos(2 * np.pi * df_analyze.index.hour / 24)
df_analyze['day_of_week'] = df_analyze.index.dayofweek
df_analyze['close_pct_3'] = df_analyze['close'].pct_change(3)
df_analyze['log_return'] = np.log(df_analyze['close'] / df_analyze['close'].shift(1))
df_analyze['close_lag_1'] = df_analyze['close'].shift(1)
df_analyze['hl_range'] = df_analyze['high'] - df_analyze['low']

df_analyze.tail()
```

Out[9]:

timestamp	open	high	low	close	volume	close_future_6	price_movement	close_future_1	candle_body_pct
2025-04-15 02:00:00	84966.20	85284.50	84697.47	85220.32	296.418309	84860.07	0	84599.99	0.432891
2025-04-15 03:00:00	85220.32	85403.63	85068.00	85365.43	345.552030	84700.03	0	84934.24	0.432351
2025-04-15 04:00:00	85365.43	85511.68	85155.07	85485.87	314.500596	84517.01	0	84966.20	0.337736
2025-04-15 05:00:00	85485.87	85855.86	85473.01	85535.48	373.851146	84599.99	0	85220.32	0.129581
2025-04-15 06:00:00	85535.48	85678.00	85362.00	85400.22	217.607356	84934.24	0	85365.43	-0.428038

5 rows × 43 columns

In [10]:

```python
print("Sebelum dilakukan handling")
print(df_analyze.info())

df_analyze.dropna(inplace=True)
print("\n---------------------------\n")
```

```python
print("Setelah dilakukan handling")
print(df_analyze.info())
```

```
Sebelum dilakukan handling
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 1000 entries, 2025-03-04 15:00:00 to 2025-04-15 06:00:00
Data columns (total 43 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   open                  1000 non-null   float64
 1   high                  1000 non-null   float64
 2   low                   1000 non-null   float64
 3   close                 1000 non-null   float64
 4   volume                1000 non-null   float64
 5   close_future_6        994 non-null    float64
 6   price_movement        1000 non-null   int64  
 7   close_future_1        997 non-null    float64
 8   candle_body_pct       1000 non-null   float64
 9   volume_change         999 non-null    float64
 10  bb_width              981 non-null    float64
 11  close_pct_1           999 non-null    float64
 12  return_lag_1          998 non-null    float64
 13  volatility_5          995 non-null    float64
 14  ema_10                1000 non-null   float64
 15  ema_20                1000 non-null   float64
 16  ema_10_rel            1000 non-null   float64
 17  ema_20_rel            1000 non-null   float64
 18  ema_cross             1000 non-null   int64  
 19  rsi                   987 non-null    float64
 20  rsi_change            981 non-null    float64
 21  bb_width_change       978 non-null    float64
 22  vol_accel             998 non-null    float64
 23  returns               999 non-null    float64
 24  atr                   1000 non-null   float64
 25  wick_upper            1000 non-null   float64
 26  wick_lower            1000 non-null   float64
 27  price_activity_ratio  989 non-null    float64
 28  volume_ratio_4h       997 non-null    float64
 29  rsi_slope             984 non-null    float64
 30  atr_change            987 non-null    float64
 31  close_momentum_6h     994 non-null    float64
 32  close_momentum_12h    988 non-null    float64
 33  close_momentum_24h    976 non-null    float64
 34  price_zscore          951 non-null    float64
 35  hour                  1000 non-null   int32  
 36  hour_sin              1000 non-null   float64
 37  hour_cos              1000 non-null   float64
 38  day_of_week           1000 non-null   int32  
 39  close_pct_3           997 non-null    float64
 40  log_return            999 non-null    float64
 41  close_lag_1           999 non-null    float64
 42  hl_range              1000 non-null   float64
dtypes: float64(39), int32(2), int64(2)
memory usage: 335.9 KB
None

----------------------------

Setelah dilakukan handling
<class 'pandas.core.frame.DataFrame'>
DatetimeIndex: 951 entries, 2025-03-06 16:00:00 to 2025-04-15 06:00:00
Data columns (total 43 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   open                  951 non-null    float64
 1   high                  951 non-null    float64
 2   low                   951 non-null    float64
 3   close                 951 non-null    float64
 4   volume                951 non-null    float64
 5   close_future_6        951 non-null    float64
 6   price_movement        951 non-null    int64  
 7   close_future_1        951 non-null    float64
 8   candle_body_pct       951 non-null    float64
 9   volume_change         951 non-null    float64
 10  bb_width              951 non-null    float64
 11  close_pct_1           951 non-null    float64
 12  return_lag_1          951 non-null    float64
 13  volatility_5          951 non-null    float64
 14  ema_10                951 non-null    float64
 15  ema_20                951 non-null    float64
 16  ema_10_rel            951 non-null    float64
 17  ema_20_rel            951 non-null    float64
 18  ema_cross             951 non-null    int64  
 19  rsi                   951 non-null    float64
```

```
 20  rsi_change           951 non-null    float64
 21  bb_width_change      951 non-null    float64
 22  vol_accel            951 non-null    float64
 23  returns              951 non-null    float64
 24  atr                  951 non-null    float64
 25  wick_upper           951 non-null    float64
 26  wick_lower           951 non-null    float64
 27  price_activity_ratio  951 non-null    float64
 28  volume_ratio_4h      951 non-null    float64
 29  rsi_slope            951 non-null    float64
 30  atr_change           951 non-null    float64
 31  close_momentum_6h    951 non-null    float64
 32  close_momentum_12h   951 non-null    float64
 33  close_momentum_24h   951 non-null    float64
 34  price_zscore         951 non-null    float64
 35  hour                 951 non-null    int32
 36  hour_sin             951 non-null    float64
 37  hour_cos             951 non-null    float64
 38  day_of_week          951 non-null    int32
 39  close_pct_3          951 non-null    float64
 40  log_return           951 non-null    float64
 41  close_lag_1          951 non-null    float64
 42  hl_range             951 non-null    float64
dtypes: float64(39), int32(2), int64(2)
memory usage: 319.5 KB
None
```

That's... quite a lot isn't it hehehe? honestly, I'm still learning and I wasn't sure which features would give the best prediction results. So I decided to try as many reasonable features as I could think of (mostly from technical indicators and price-related patterns). Later on, I can use feature selection or model evaluation to figure out which ones actually help. For now, it's more like learning by doing and seeing what works.

Model Machine Learning

You all know about LSTM or Long Short Term Memory? i will use that in this prediction, reason? i dont know, ups sorry, i know the reason hehehe. Because I think instead of using linear regression because the current condition of bitcoin is very volatile and linear regression will be overwhelmed in predicting it, therefore I choose LSTM because it can handle volatility (but I also know that LSTM has the potential for overfitting especially the features I use a lot lol).

For this project, I'm predicting two targets: the current price, and the price from six hours ago (by shifting the price column upward). My idea is to give the model a short-term and slightly mid-term perspective, so it can learn both recent patterns and a bit of context from the past.

In [11]:
```
from sklearn.preprocessing import MinMaxScaler
from keras.models import Model
from keras.layers import Input, LSTM, Dense, Dropout
from keras.callbacks import EarlyStopping
from sklearn.model_selection import TimeSeriesSplit
from sklearn.feature_selection import SelectKBest, f_regression
```

In [12]:
```
selected_features = [
    'open', 'high', 'low', 'volume',
    'candle_body_pct', 'volume_change', 'bb_width', 'close_pct_1', 'return_lag_1',
    'volatility_5', 'ema_10_rel', 'ema_20_rel',
    'rsi', 'rsi_change', 'rsi_slope',
    'bb_width_change', 'vol_accel', 'returns', 'atr', 'atr_change',
    'wick_upper', 'wick_lower', 'price_activity_ratio', 'volume_ratio_4h',
    'close_momentum_6h', 'close_momentum_12h', 'close_momentum_24h',
    'price_zscore', 'log_return', 'hl_range'
]

selector = SelectKBest(f_regression, k=20)
X_selected = selector.fit_transform(df_analyze[selected_features], df_analyze['close'])

selected_features = [selected_features[i] for i in selector.get_support(indices=True)]
print("Selected features:", selected_features)

y_multi = df_analyze[['close', 'close_future_6']].dropna()

y_data_reg = df_analyze['close'].values.reshape(-1, 1)
y_data_clf = df_analyze['price_movement'].values

scaler_X = MinMaxScaler()
scaler_y = MinMaxScaler()

X_aligned = df_analyze.loc[y_multi.index, selected_features].values

X_scaled = scaler_X.fit_transform(X_aligned)
y_scaled_reg = scaler_y.fit_transform(y_data_reg)
y_scaled_multi = scaler_y.fit_transform(y_multi.values)
```

```
df_scaled = np.hstack([y_scaled_multi, X_scaled])

df_scaled
```

```
Selected features: ['open', 'high', 'low', 'volume', 'bb_width', 'close_pct_1', 'volatility_5', 'ema_10_rel', 'e
ma_20_rel', 'rsi', 'atr', 'atr_change', 'wick_upper', 'wick_lower', 'close_momentum_6h', 'close_momentum_12h', '
close_momentum_24h', 'price_zscore', 'log_return', 'hl_range']
```

Out[12]:

```
array([[0.92862374, 0.99635296, 1.        , ..., 0.58766014, 0.33924641,
        0.27392325],
       [0.88456255, 1.        , 0.90668462, ..., 0.53909206, 0.42829386,
        0.20237884],
       [0.87106632, 0.92463536, 0.8636644 , ..., 0.51458006, 0.48222187,
        0.11466484],
       ...,
       [0.68222856, 0.58639533, 0.6585832 , ..., 0.79334915, 0.52041083,
        0.04984241],
       [0.68540418, 0.59141742, 0.66611063, ..., 0.80324004, 0.5120529 ,
        0.05386488],
       [0.67674595, 0.6116468 , 0.66921123, ..., 0.76191743, 0.49026712,
        0.04361709]])
```

I split the data manually, I don't use train-test-split because it will make the prediction overfitting (because the past will learn the future, it's crazy, it doesn't make sense). By the way, I split the data into two parts, first regression and classification, I just want the model to have more information about the price (and to understand about volatility).

In [13]:

```
window_size = 60

def create_sequences(X, y, window=60):
    Xs, ys = [], []
    for i in range(window, len(X)):
        Xs.append(X[i - window:i])
        ys.append(y[i])
    return np.array(Xs), np.array(ys)

X_seq, y_seq_reg = create_sequences(X_scaled, y_scaled_reg, window=window_size)
_, y_seq_clf = create_sequences(X_scaled, y_data_clf, window=window_size)

X_seq, y_seq = create_sequences(X_scaled, y_scaled_multi, window_size)

split_index = int(len(X_seq) * 0.7)
X_train, X_test = X_seq[:split_index], X_seq[split_index:]
y_train_reg, y_test_reg = y_seq_reg[:split_index], y_seq_reg[split_index:]
y_train_clf, y_test_clf = y_seq_clf[:split_index], y_seq_clf[split_index:]
```

In [14]:

```
input_layer = Input(shape=(X_train.shape[1], X_train.shape[2]))
x = LSTM(128, return_sequences=True)(input_layer)
x = LSTM(64)(x)
output_reg = Dense(1, name='regression')(x)
output_clf = Dense(1, activation='sigmoid', name='classification')(x)

model = Model(inputs=input_layer, outputs=[output_reg, output_clf])
model.compile(
    optimizer='adam',
    loss={'regression': 'mse', 'classification': 'binary_crossentropy'},
    metrics={'regression': 'mae', 'classification': 'accuracy'}
)

model.summary()

es = EarlyStopping(patience=5, restore_best_weights=True)
model.fit(
    X_train, {'regression': y_train_reg, 'classification': y_train_clf},
    validation_split=0.2,
    epochs=50,
    batch_size=32,
    callbacks=[es]
)
```

Model: "functional"

Layer (type)	Output Shape	Param #	Connected to
input_layer (InputLayer)	(None, 60, 20)	0	-
lstm (LSTM)	(None, 60, 128)	76,288	input_layer[0][0]
lstm_1 (LSTM)	(None, 64)	49,408	lstm[0][0]
regression (Dense)	(None, 1)	65	lstm_1[0][0]
classification (Dense)	(None, 1)	65	lstm_1[0][0]

Total params: 125,826 (491.51 KB)

Trainable params: 125,826 (491.51 KB)

Non-trainable params: 0 (0.00 B)

```
Epoch 1/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 14s 164ms/step - classification_accuracy: 0.5096 - classification_loss: 0.7013 - loss: 0.8008 - regression_loss: 0.0995 - regression_mae: 0.2399 - val_classification_accuracy: 0.5520 - val_classification_loss: 0.6900 - val_loss: 0.7071 - val_regression_loss: 0.0173 - val_regression_mae: 0.1217
Epoch 2/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 4s 129ms/step - classification_accuracy: 0.5472 - classification_loss: 0.6882 - loss: 0.6958 - regression_loss: 0.0075 - regression_mae: 0.0706 - val_classification_accuracy: 0.4480 - val_classification_loss: 0.6951 - val_loss: 0.7026 - val_regression_loss: 0.0070 - val_regression_mae: 0.0707
Epoch 3/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 122ms/step - classification_accuracy: 0.5605 - classification_loss: 0.6817 - loss: 0.6866 - regression_loss: 0.0051 - regression_mae: 0.0567 - val_classification_accuracy: 0.5520 - val_classification_loss: 0.6870 - val_loss: 0.6908 - val_regression_loss: 0.0050 - val_regression_mae: 0.0575
Epoch 4/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 114ms/step - classification_accuracy: 0.5246 - classification_loss: 0.6901 - loss: 0.6955 - regression_loss: 0.0052 - regression_mae: 0.0579 - val_classification_accuracy: 0.5440 - val_classification_loss: 0.6812 - val_loss: 0.6834 - val_regression_loss: 0.0026 - val_regression_mae: 0.0397
Epoch 5/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 112ms/step - classification_accuracy: 0.6102 - classification_loss: 0.6626 - loss: 0.6683 - regression_loss: 0.0057 - regression_mae: 0.0573 - val_classification_accuracy: 0.5520 - val_classification_loss: 0.7190 - val_loss: 0.7196 - val_regression_loss: 0.0028 - val_regression_mae: 0.0429
Epoch 6/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 142ms/step - classification_accuracy: 0.5700 - classification_loss: 0.6713 - loss: 0.6800 - regression_loss: 0.0086 - regression_mae: 0.0757 - val_classification_accuracy: 0.4560 - val_classification_loss: 0.6893 - val_loss: 0.6926 - val_regression_loss: 0.0023 - val_regression_mae: 0.0369
Epoch 7/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 157ms/step - classification_accuracy: 0.5878 - classification_loss: 0.6609 - loss: 0.6651 - regression_loss: 0.0042 - regression_mae: 0.0512 - val_classification_accuracy: 0.5440 - val_classification_loss: 0.6699 - val_loss: 0.6737 - val_regression_loss: 0.0042 - val_regression_mae: 0.0533
Epoch 8/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 124ms/step - classification_accuracy: 0.6861 - classification_loss: 0.6205 - loss: 0.6273 - regression_loss: 0.0067 - regression_mae: 0.0668 - val_classification_accuracy: 0.5840 - val_classification_loss: 0.6788 - val_loss: 0.6827 - val_regression_loss: 0.0037 - val_regression_mae: 0.0490
Epoch 9/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 114ms/step - classification_accuracy: 0.7097 - classification_loss: 0.5916 - loss: 0.5959 - regression_loss: 0.0041 - regression_mae: 0.0475 - val_classification_accuracy: 0.5920 - val_classification_loss: 0.7235 - val_loss: 0.7270 - val_regression_loss: 0.0035 - val_regression_mae: 0.0481
Epoch 10/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 114ms/step - classification_accuracy: 0.7283 - classification_loss: 0.5557 - loss: 0.5598 - regression_loss: 0.0043 - regression_mae: 0.0513 - val_classification_accuracy: 0.6560 - val_classification_loss: 0.6578 - val_loss: 0.6654 - val_regression_loss: 0.0068 - val_regression_mae: 0.0695
Epoch 11/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 114ms/step - classification_accuracy: 0.7283 - classification_loss: 0.5642 - loss: 0.5679 - regression_loss: 0.0039 - regression_mae: 0.0471 - val_classification_accuracy: 0.5760 - val_classification_loss: 0.6783 - val_loss: 0.6869 - val_regression_loss: 0.0094 - val_regression_mae: 0.0898
Epoch 12/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 209ms/step - classification_accuracy: 0.7120 - classification_loss: 0.5624 - loss: 0.5724 - regression_loss: 0.0102 - regression_mae: 0.0862 - val_classification_accuracy: 0.7280 - val_classification_loss: 0.6117 - val_loss: 0.6150 - val_regression_loss: 0.0029 - val_regression_mae: 0.0413
Epoch 13/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 114ms/step - classification_accuracy: 0.7597 - classification_loss: 0.5276 - loss: 0.5338 - regression_loss: 0.0064 - regression_mae: 0.0645 - val_classification_accuracy: 0.7120 - val_classification_loss: 0.6162 - val_loss: 0.6204 - val_regression_loss: 0.0040 - val_regression_mae: 0.0524
Epoch 14/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 115ms/step - classification_accuracy: 0.7548 - classification_loss: 0.5003 - loss: 0.5045 - regression_loss: 0.0038 - regression_mae: 0.0494 - val_classification_accuracy: 0.6160 - val_classification_loss: 0.6670 - val_loss: 0.6698 - val_regression_loss: 0.0028 - val_regression_mae: 0.0429
Epoch 15/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 127ms/step - classification_accuracy: 0.7348 - classification_loss: 0.5382 - loss: 0.5416 - regression_loss: 0.0033 - regression_mae: 0.0461 - val_classification_accuracy: 0.7120 - val_classification_loss: 0.5571 - val_loss: 0.5597 - val_regression_loss: 0.0015 - val_regression_mae: 0.0298
Epoch 16/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 115ms/step - classification_accuracy: 0.7961 - classification_loss: 0.4520 - loss: 0.4546 - regression_loss: 0.0027 - regression_mae: 0.0418 - val_classification_accuracy: 0.7280 - val_classifica
```

```
tion_loss: 0.5659 - val_loss: 0.5699 - val_regression_loss: 0.0034 - val_regression_mae: 0.0451
Epoch 17/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 162ms/step - classification_accuracy: 0.7955 - classification_loss: 0.4296 - loss: 0.4330 - regression_loss: 0.0033 - regression_mae: 0.0426 - val_classification_accuracy: 0.7600 - val_classification_loss: 0.5319 - val_loss: 0.5368 - val_regression_loss: 0.0027 - val_regression_mae: 0.0382
Epoch 18/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 164ms/step - classification_accuracy: 0.7552 - classification_loss: 0.4941 - loss: 0.5000 - regression_loss: 0.0057 - regression_mae: 0.0603 - val_classification_accuracy: 0.7360 - val_classification_loss: 0.5200 - val_loss: 0.5229 - val_regression_loss: 0.0020 - val_regression_mae: 0.0347
Epoch 19/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 117ms/step - classification_accuracy: 0.8369 - classification_loss: 0.3931 - loss: 0.3988 - regression_loss: 0.0055 - regression_mae: 0.0580 - val_classification_accuracy: 0.7680 - val_classification_loss: 0.5104 - val_loss: 0.5161 - val_regression_loss: 0.0036 - val_regression_mae: 0.0518
Epoch 20/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 115ms/step - classification_accuracy: 0.8316 - classification_loss: 0.3664 - loss: 0.3683 - regression_loss: 0.0030 - regression_mae: 0.0416 - val_classification_accuracy: 0.7920 - val_classification_loss: 0.4788 - val_loss: 0.4858 - val_regression_loss: 0.0051 - val_regression_mae: 0.0618
Epoch 21/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 118ms/step - classification_accuracy: 0.8730 - classification_loss: 0.3268 - loss: 0.3298 - regression_loss: 0.0030 - regression_mae: 0.0449 - val_classification_accuracy: 0.7440 - val_classification_loss: 0.4634 - val_loss: 0.4671 - val_regression_loss: 0.0020 - val_regression_mae: 0.0314
Epoch 22/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 118ms/step - classification_accuracy: 0.8650 - classification_loss: 0.3296 - loss: 0.3334 - regression_loss: 0.0038 - regression_mae: 0.0489 - val_classification_accuracy: 0.7280 - val_classification_loss: 0.4763 - val_loss: 0.4822 - val_regression_loss: 0.0031 - val_regression_mae: 0.0418
Epoch 23/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 183ms/step - classification_accuracy: 0.8412 - classification_loss: 0.3569 - loss: 0.3615 - regression_loss: 0.0040 - regression_mae: 0.0501 - val_classification_accuracy: 0.8000 - val_classification_loss: 0.4643 - val_loss: 0.4687 - val_regression_loss: 0.0029 - val_regression_mae: 0.0432
Epoch 24/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 132ms/step - classification_accuracy: 0.8949 - classification_loss: 0.2955 - loss: 0.2986 - regression_loss: 0.0035 - regression_mae: 0.0466 - val_classification_accuracy: 0.7680 - val_classification_loss: 0.4909 - val_loss: 0.5006 - val_regression_loss: 0.0070 - val_regression_mae: 0.0736
Epoch 25/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 117ms/step - classification_accuracy: 0.8499 - classification_loss: 0.3112 - loss: 0.3154 - regression_loss: 0.0041 - regression_mae: 0.0514 - val_classification_accuracy: 0.7680 - val_classification_loss: 0.4427 - val_loss: 0.4462 - val_regression_loss: 0.0034 - val_regression_mae: 0.0435
Epoch 26/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 117ms/step - classification_accuracy: 0.8677 - classification_loss: 0.3085 - loss: 0.3115 - regression_loss: 0.0026 - regression_mae: 0.0398 - val_classification_accuracy: 0.8000 - val_classification_loss: 0.4544 - val_loss: 0.4568 - val_regression_loss: 0.0016 - val_regression_mae: 0.0302
Epoch 27/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 117ms/step - classification_accuracy: 0.8637 - classification_loss: 0.2921 - loss: 0.2943 - regression_loss: 0.0020 - regression_mae: 0.0349 - val_classification_accuracy: 0.8160 - val_classification_loss: 0.4979 - val_loss: 0.4999 - val_regression_loss: 0.0026 - val_regression_mae: 0.0381
Epoch 28/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 148ms/step - classification_accuracy: 0.8973 - classification_loss: 0.2762 - loss: 0.2781 - regression_loss: 0.0025 - regression_mae: 0.0399 - val_classification_accuracy: 0.7760 - val_classification_loss: 0.4983 - val_loss: 0.5030 - val_regression_loss: 0.0018 - val_regression_mae: 0.0317
Epoch 29/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 3s 168ms/step - classification_accuracy: 0.8626 - classification_loss: 0.2943 - loss: 0.2959 - regression_loss: 0.0019 - regression_mae: 0.0344 - val_classification_accuracy: 0.7840 - val_classification_loss: 0.4813 - val_loss: 0.4853 - val_regression_loss: 0.0020 - val_regression_mae: 0.0340
Epoch 30/50
16/16 ━━━━━━━━━━━━━━━━━━━━ 2s 115ms/step - classification_accuracy: 0.8965 - classification_loss: 0.2828 - loss: 0.2852 - regression_loss: 0.0026 - regression_mae: 0.0412 - val_classification_accuracy: 0.7680 - val_classification_loss: 0.4794 - val_loss: 0.4861 - val_regression_loss: 0.0048 - val_regression_mae: 0.0603
```

Out[14]: <keras.src.callbacks.history.History at 0x7a93dc7a0f50>

In [15]:

```python
y_pred_reg, y_pred_clf = model.predict(X_test)
y_pred_reg_2d = np.concatenate([y_pred_reg, np.zeros_like(y_pred_reg)], axis=1)
y_pred_reg_inv = scaler_y.inverse_transform(y_pred_reg_2d)[:, 0]

y_test_reg_2d = np.concatenate([y_test_reg, np.zeros_like(y_test_reg)], axis=1)
y_test_reg_inv = scaler_y.inverse_transform(y_test_reg_2d)[:, 0]
```

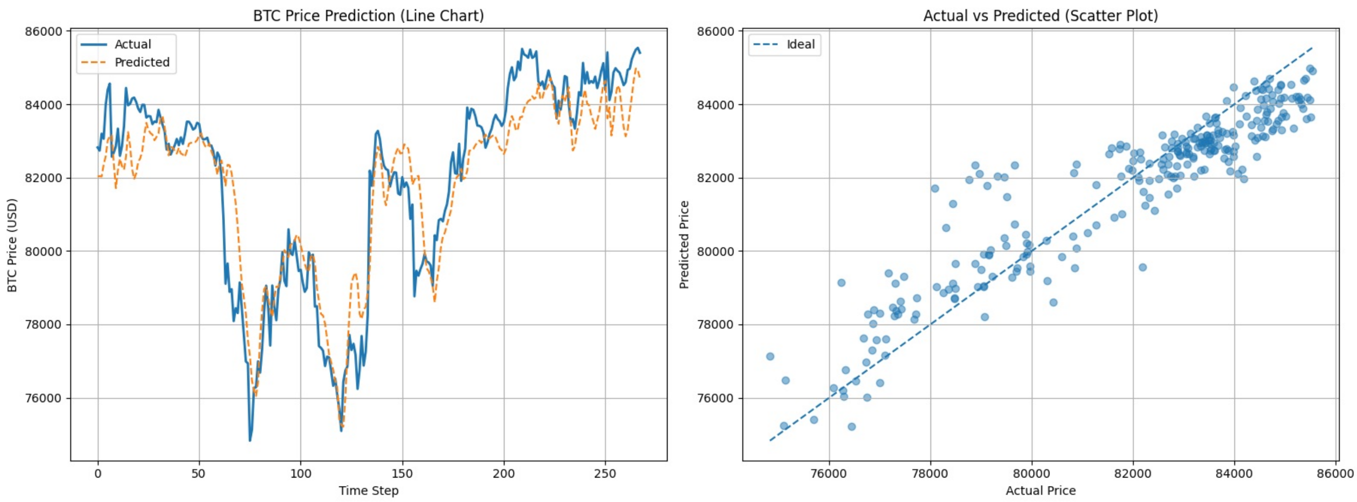
```
9/9 ━━━━━━━━━━━━━━━━━━━━ 1s 76ms/step
```

In [16]:

```python
from sklearn.metrics import mean_absolute_error, median_absolute_error, r2_score, mean_absolute_percentage_erro

mae = mean_absolute_error(y_test_reg_inv, y_pred_reg_inv)
medae = median_absolute_error(y_test_reg_inv, y_pred_reg_inv)
mape = np.mean(np.abs((y_test_reg_inv - y_pred_reg_inv) / y_test_reg_inv)) * 100
r2 = r2_score(y_test_reg_inv, y_pred_reg_inv)

print('Regression Evaluation')
print(f"MAE   : {mae:.4f}")
print(f"MedAE : {medae:.4f}")
print(f"MAPE: {mape:.2f}%")
print(f"R^2   : {r2:.4f}")
print('------------------')

fig, axs = plt.subplots(1, 2, figsize=(16, 6))
```

```python
axs[0].plot(y_test_reg_inv[:360], label='Actual', linewidth=2)
axs[0].plot(y_pred_reg_inv[:360], label='Predicted', linestyle='--')
axs[0].set_title('BTC Price Prediction (Line Chart)')
axs[0].set_xlabel('Time Step')
axs[0].set_ylabel('BTC Price (USD)')
axs[0].legend()
axs[0].grid(True)

axs[1].scatter(y_test_reg_inv, y_pred_reg_inv, alpha=0.5)
axs[1].plot([min(y_test_reg_inv), max(y_test_reg_inv)],
            [min(y_test_reg_inv), max(y_test_reg_inv)], '--', label='Ideal')
axs[1].set_title('Actual vs Predicted (Scatter Plot)')
axs[1].set_xlabel('Actual Price')
axs[1].set_ylabel('Predicted Price')
axs[1].legend()
axs[1].grid(True)

plt.tight_layout()
plt.show()
```

```
Regression Evaluation
MAE   : 814.0456
MedAE : 652.1306
MAPE: 1.00%
R^2   : 0.8538
------------------
```



Wait...

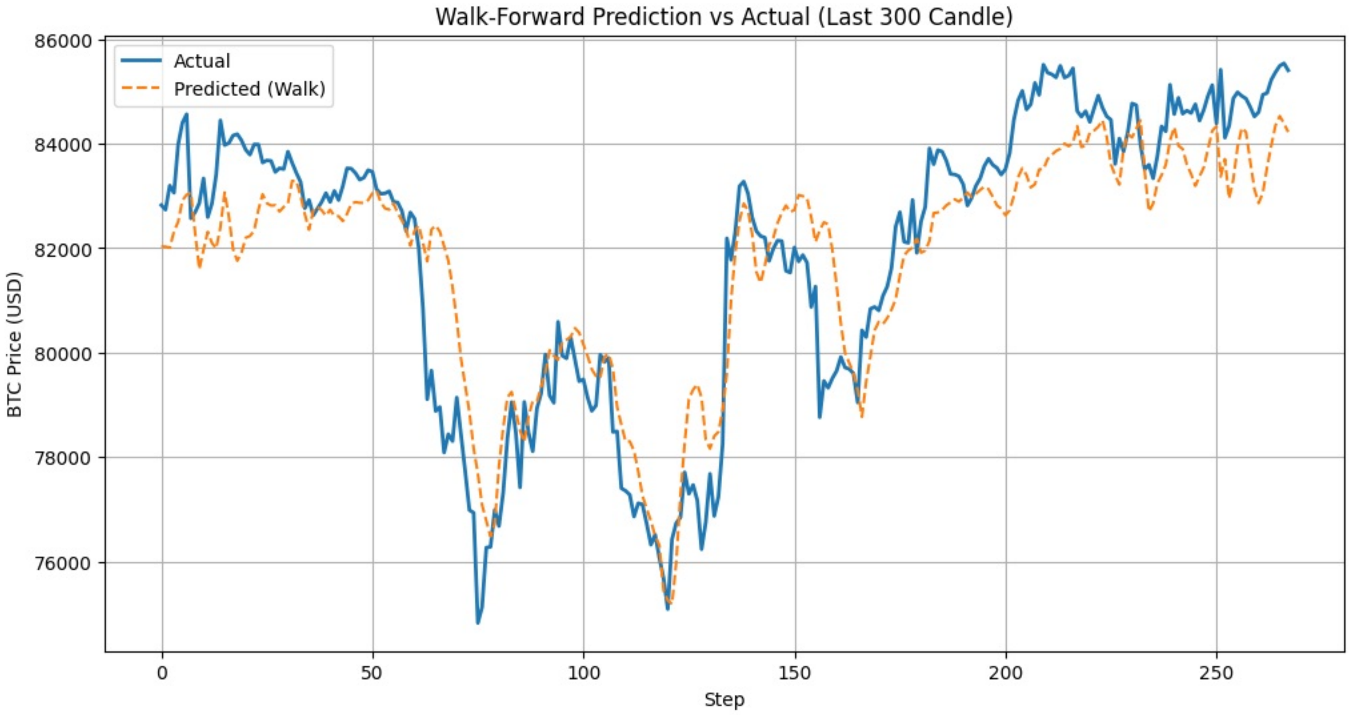
Is the model actually good or is there a problem? I'm always skeptical of the models I build, let's do a walk forward test.

In [17]:
```python
walk_preds = []
walk_truth = []

input_seq = X_test[0].copy()

for i in range(len(X_test)):
    pred_reg, pred_clf = model.predict(input_seq[np.newaxis, :, :], verbose=0)
    pred = pred_reg[0][0]
    walk_preds.append(pred)
    walk_truth.append(y_test_reg[i][0])

    if i + 1 < len(X_test):
        next_row = X_test[i + 1, -1, :]
        next_row_with_pred = next_row.copy()
        next_row_with_pred[0] = pred
        input_seq = np.vstack([input_seq[1:], [next_row_with_pred]])
```

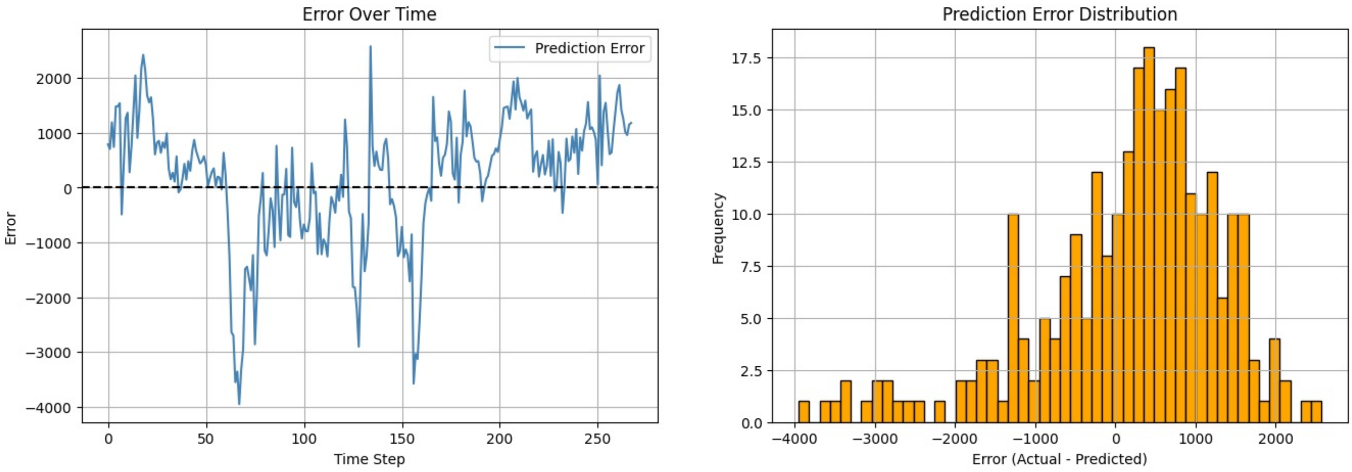
In [18]:
```python
walk_preds_2d = np.concatenate([np.array(walk_preds).reshape(-1, 1), np.zeros_like(np.array(walk_preds).reshape
walk_preds_inv = scaler_y.inverse_transform(walk_preds_2d)[:, 0]
walk_truth_2d = np.concatenate([np.array(walk_truth).reshape(-1, 1), np.zeros_like(np.array(walk_truth).reshape
walk_truth_inv = scaler_y.inverse_transform(walk_truth_2d)[:, 0]

mae_walk = mean_absolute_error(walk_truth_inv, walk_preds_inv)
mape_walk = np.mean(np.abs((walk_truth_inv - walk_preds_inv) / walk_truth_inv)) * 100
r2_walk = r2_score(walk_truth_inv, walk_preds_inv)

print(f"[Walk-Forward] MAE  : {mae_walk:.2f}")
print(f"[Walk-Forward] MAPE : {mape_walk:.2f}%")
print(f"[Walk-Forward] R²   : {r2_walk:.4f}")
```

```
[Walk-Forward] MAE  : 926.88
[Walk-Forward] MAPE : 1.14%
[Walk-Forward] R²   : 0.8172
```

In [19]:
```python
plt.figure(figsize=(12, 6))
plt.plot(walk_truth_inv[:300], label='Actual', linewidth=2)
plt.plot(walk_preds_inv[:300], label='Predicted (Walk)', linestyle='--')
plt.title('Walk-Forward Prediction vs Actual (Last 300 Candle)')
plt.xlabel('Step')
plt.ylabel('BTC Price (USD)')
plt.legend()
plt.grid(True)
plt.show()
```

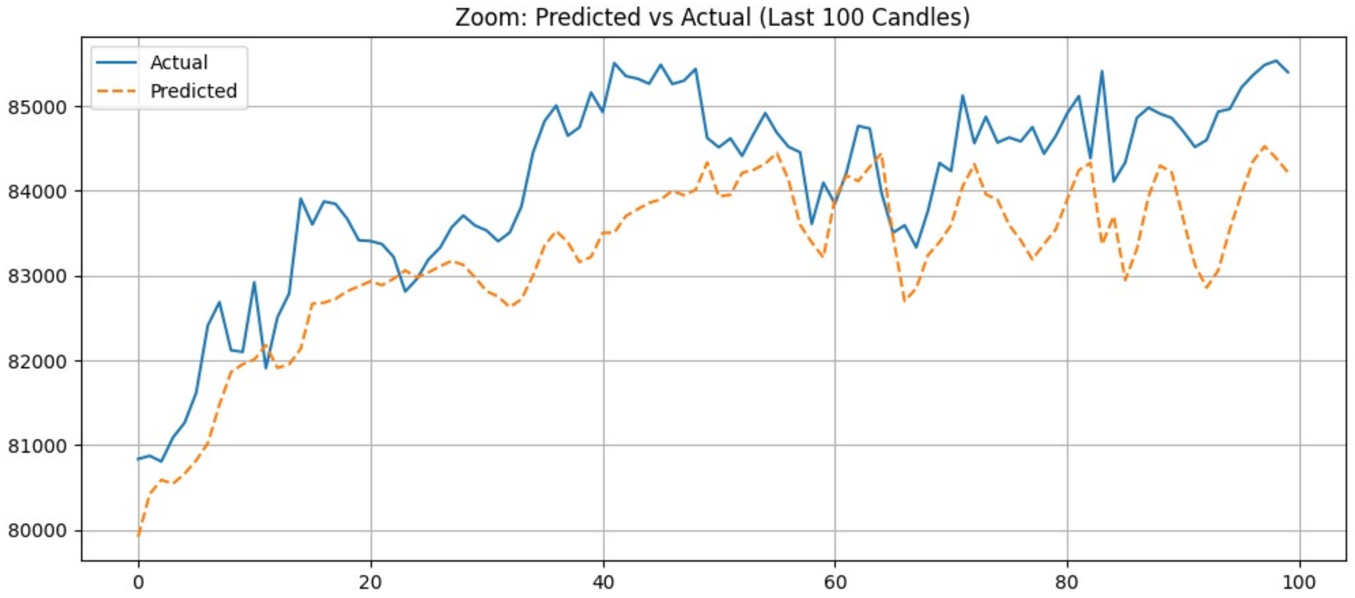


In [20]:
```python
error = walk_truth_inv.flatten() - walk_preds_inv.flatten()

fig, axs = plt.subplots(1, 2, figsize=(16, 5))

axs[0].plot(error, label='Prediction Error', color='steelblue')
axs[0].axhline(0, color='black', linestyle='--')
axs[0].set_title("Error Over Time")
axs[0].set_xlabel("Time Step")
axs[0].set_ylabel("Error")
axs[0].legend()
axs[0].grid(True)

axs[1].hist(error, bins=50, color='orange', edgecolor='black')
axs[1].set_title("Prediction Error Distribution")
axs[1].set_xlabel("Error (Actual - Predicted)")
axs[1].set_ylabel("Frequency")
axs[1].grid(True)

plt.show()
```

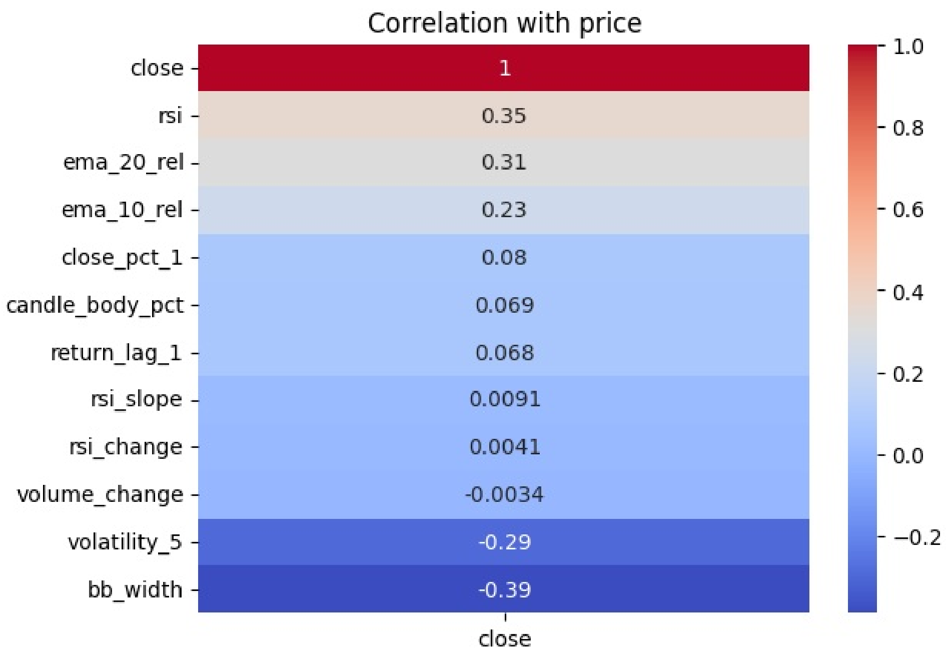


In [21]:
```python
n = 100
plt.figure(figsize=(12, 5))
```

```python
plt.plot(walk_truth_inv[-n:], label="Actual")
plt.plot(walk_preds_inv[-n:], label="Predicted", linestyle="--")
plt.title("Zoom: Predicted vs Actual (Last 100 Candles)")
plt.grid(True)
plt.legend()
plt.show()
```



In [22]:
```python
import seaborn as sns

selected_features = ['candle_body_pct','bb_width','close_pct_1','return_lag_1','volatility_5','volume_change','
target_correlation = df_analyze[selected_features].corr()

sns.heatmap(target_correlation[['close']].sort_values(by='close', ascending=False), annot=True, cmap='coolwarm'
plt.title("Correlation with price")
plt.show()
```



Forecasting

This part is more interesting than the previous part, because we can earn money if our prediction is correct hehehe. Kidding hehehe. Actually I don't want to trust the model because there are too many simplifications here, and I know quant trade has more data and more complicated models to understand bitcoin.

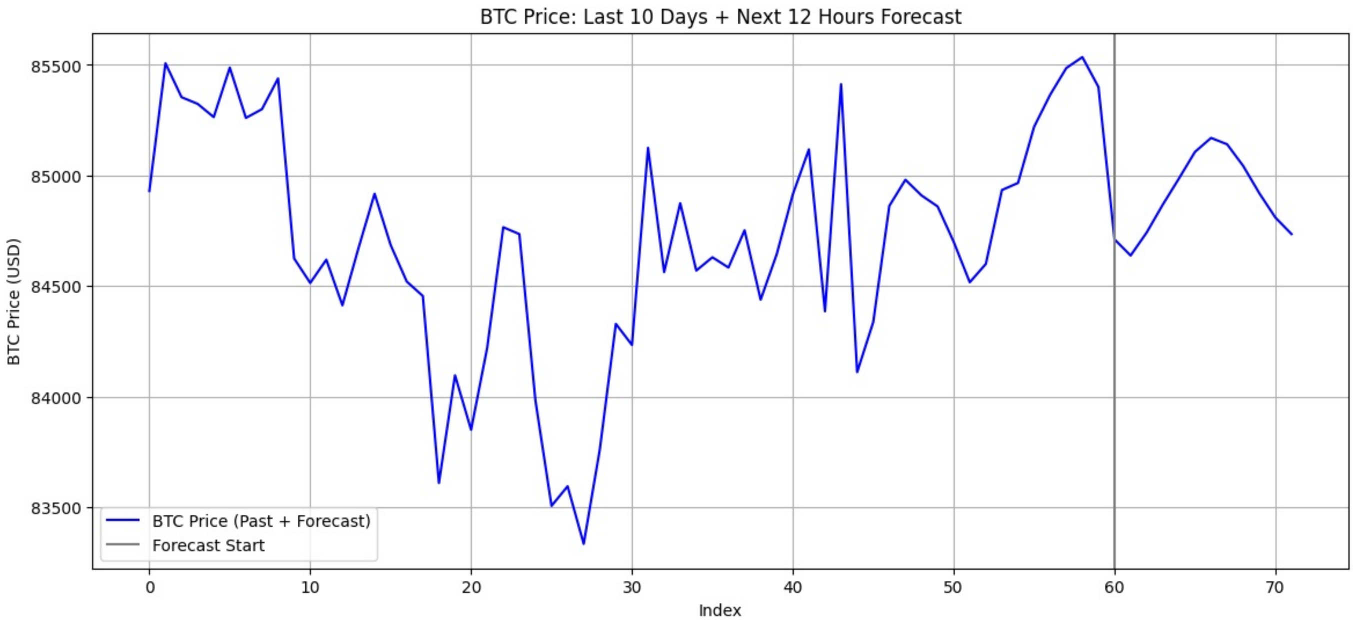
So this is like a disclaimer to understand the context, this part doesn't need to be fully believed because what I'm doing here is just to train my thinking and how I can apply the knowledge I've gained so far in Data Science. Just for learning.

In [23]:
```python
forecast = []
input_seq = X_test[-1].copy()

for _ in range(12):
    pred_reg, pred_clf = model.predict(input_seq[np.newaxis, :, :], verbose=0)
    pred = pred_reg[0][0]
```

```
    forecast.append(pred)

    new_row = np.zeros_like(input_seq[0])
    new_row[0] = pred
    new_row[1:] = input_seq[-1, 1:]

    input_seq = np.vstack([input_seq[1:], new_row])

forecast_scaled = np.array(forecast).reshape(-1, 1)
forecast_scaled_2d = np.concatenate([forecast_scaled, np.zeros_like(forecast_scaled)], axis=1)
forecast_actual = scaler_y.inverse_transform(forecast_scaled_2d)[:, 0].flatten()
```

In [24]:
```
print("BTC price forecast (within the next 12 candles):")
forecast_actual = pd.DataFrame(forecast_actual, columns=['Price'])

forecast_actual.index = [i for i in range(1, 13)]

print(forecast_actual)

historical = df_analyze['close'].iloc[-60:].values
combined = np.concatenate([historical, forecast_actual['Price'].values])

plt.figure(figsize=(14, 6))
plt.plot(combined, label='BTC Price (Past + Forecast)', color='blue')
plt.axvline(x=60, color='gray', label='Forecast Start')
plt.title('BTC Price: Last 10 Days + Next 12 Hours Forecast')
plt.xlabel('Index')
plt.ylabel('BTC Price (USD)')
plt.legend()
plt.grid(True)
plt.show()
```

```
BTC price forecast (within the next 12 candles):
           Price
1   84711.046875
2   84638.000000
3   84742.328125
4   84868.296875
5   84985.921875
6   85106.773438
7   85169.953125
8   85141.023438
9   85043.062500
10  84919.750000
11  84809.750000
12  84735.085938
```



Sentiment Analysis

In the world of trading, there are actually two different groups, one is people who just analyze the price (technical analysis), the other is people who analyze the macro-micro economy to understand what will happen to the price (fundamental analysis). And I want to combine both of them into one group here (to help me decide what to do with the current price, whether buy, sell or hold).

Actually I wanted to get the data from twitter but I couldn't get it, so I will get from two sources, first from CoinDesk and second from CryptoPanic

In [25]:
```
import requests
```

```python
from bs4 import BeautifulSoup

def scrape_coindesk_with_content(max_articles=10):
    base_url = "https://www.coindesk.com/"
    response = requests.get(base_url)
    soup = BeautifulSoup(response.content, 'html.parser')

    articles = []
    seen_urls = set()

    for link_tag in soup.find_all('a', href=True):
        href = link_tag['href']
        full_url = href if href.startswith("http") else f"https://www.coindesk.com{href}"
        if "/" in href and "video" not in href and full_url not in seen_urls and href.startswith(('/markets', ',
            seen_urls.add(full_url)
            try:
                article_page = requests.get(full_url)
                article_soup = BeautifulSoup(article_page.content, 'html.parser')

                title_tag = article_soup.find(['h1', 'h2'])
                title = title_tag.get_text(strip=True) if title_tag else "No title"
                paragraphs = article_soup.find_all('p')
                content = " ".join(p.get_text(strip=True) for p in paragraphs[:5])

                articles.append({
                    'url': full_url,
                    'title': title,
                    'content': content
                })

                if len(articles) >= max_articles:
                    break

            except Exception as e:
                print(f"Error fetching {full_url}: {e}")
                continue

    return articles

news_articles = scrape_coindesk_with_content(25)
news_articles[0:3]
```

Out[25]:

```
[{'url': 'https://www.coindesk.com/markets/2025/04/15/dogecoin-slumps-3-bitcoin-steady-around-usd85k-as-traders
-fear-u-s-recession',
  'title': 'Dogecoin Slumps 3%, Bitcoin Steady Around $85K as Traders Fear U.S. Recession',
  'content': "Dogecoin (DOGE) shed 3% while bitcoin (BTC) and ether (ETH) remained flat in the past 24 hours as
tariff concerns gradually subsided among traders, though fears of a U.S. recession increased in betting markets
. “Prominent financial figures have started to warn that the U.S. is heading into an imminent recession, with b
etting markets placing 40% to 60% odds of one happening in 2025,” Augustine Fan, head of insights at SignalPlus
, told CoinDesk in a Telegram message. “Our view is that it probably doesn't matter, as sentiment often frames
reality, not the other way around.” “As such, crypto has benefited from the recent shake-out, as equities have
been realizing higher volatility than Bitcoin through the risk-off move. A beggar-thy-neighbour policy with tar
iffs has pushed spot gold to ATHs, with BTC finally regaining some of its long-lost 'store of value' narrative,
” Fan added. Crypto majors tracked by the broad-based CoinDesk 20 (CD20) slid nearly 2%, data shows, with DOGE
leading losses. Solana’s SOL, tron (TRX) and Cardano’s ADA lost as much as 2.5%, BNB Chain’s BNB and xrp (XRP)
were little changed as bitcoin clung to the $85,000 level. Mantra’s OM token showed a 20% rise over the past 24
hours to trade at 63 cents in Asian morning hours Tuesday, following a bizarre sell-off that saw it lose 90% wi
thin an hour late Sunday. A recovery plan is in the works, its CEO said in an interview following the plunge, t
hough market watchers remain sceptical of any promises."},
 {'url': 'https://www.coindesk.com/business/2025/04/14/nomura-s-laser-digital-denies-involvement-in-mantra-cras
h',
  'title': "Nomura's Laser Digital Denies Involvement in Mantra Crash",
  'content': 'Switzerland-based trading firm Laser Digital, which is part of the Nomura Group, has denied any i
nvolvement in the Mantra token flash crash that saw OM lose lose 90% of its value. "Assertions circulating on s
ocial media that link Laser to \'investor selling\' are factually incorrect and misleading," thefirm wrote on X
. Laser Digital went on to share its controlled Mantra wallet addresses, none of which show deposits to exchang
es or selling activity. Speculation remains rife over why OM collapsed so violently. The Mantra team insist it
was due to wider market pressures and centralized exchanges forcibly closing positions, which led to a liquidat
ion cascade. OKX stated that the price volatility occurred due to a spike in trading volume coupled with an ini
tial price decline across various exchanges out side of OKX, before spreading to the wider market.'},
 {'url': 'https://www.coindesk.com/markets/2025/04/14/bitcoin-facing-cloud-resistance-at-usd85k-neutralized-ris
k-reward-for-bulls',
  'title': "Bitcoin Faces 'Cloud Resistance' at $85K, Neutralizes Risk-Reward for Bulls: Godbole",
  'content': 'This is a daily technical analysis by CoinDesk analyst and Chartered Market Technician Omkar Godb
ole. In markets, securing the best entry point is often half the battle, as timing and level significantly infl
uence success by skewing the risk-reward ratio in traders\' favor. While bitcoin\'s (BTC) near-term outlook may
appear constructive withincreased demandfor bullish bets in the options market, the cryptocurrency\'s proximity
to key resistance that capped the upside in recent months means the risk-reward profile for those looking to ca
pitalize on the bullish prospects is less favorable. Since Saturday, BTC has been pushing against the lower bou
ndary of the "Ichimoku cloud" at around $85K. Developed by a Japanese journalist in the 1960s, the Ichimoku clo
ud is a technical analysis indicator that offers a comprehensive view of market momentum, support, and resistan
ce levels. The indicator comprises five lines: Leading Span A, Leading Span B, Conversion Line or Tenkan-Sen (T
), Base Line or Kijun-Sen (K) and a lagging closing price line.'}]
```

In [26]:
```python
api_key = "api_key"

base_url = "https://cryptopanic.com/api/v1/posts/"

params = {
    'auth_token': api_key,
    'filter': 'trending',
    'currencies': 'BTC',
    'regions': 'en',
    'kind': 'news',
    'public': True
}

response = requests.get(base_url, params=params)
news_data = []

if response.status_code == 200:
    data = response.json()
    for item in data['results']:
        title = item['title']
        url = item['url']
        source = item['source']['title']
        created_at = item['created_at']

        if 'currencies' in item:
            currencies = ', '.join([c['code'] for c in item['currencies']])
        else:
            currencies = ''


        news_item = {
            'judul': title,
            'url': url,
            'sumber': source,
            'waktu': created_at,
            'mata_uang': currencies,
            'content':title
        }

        news_data.append(news_item)

news_data[0:3]
```

Out[26]:
```
[{'judul': 'MicroStrategy Acquires 3,459 Bitcoins for $285.8 Million, Total Holdings Reach 531,644 BTC',
  'url': 'https://cryptopanic.com/news/21072568/MicroStrategy-Acquires-3459-Bitcoins-for-2858-Million-Total-Holdings-Reach-531644-BTC?mtm_campaign=API-OFA',
  'sumber': 'DeFi News',
  'waktu': '2025-04-14T14:30:40Z',
  'mata_uang': 'BTC',
  'content': 'MicroStrategy Acquires 3,459 Bitcoins for $285.8 Million, Total Holdings Reach 531,644 BTC'},
 {'judul': 'Saylor’s Strategy adds 3,459 Bitcoin, now holds 531,644 BTC',
  'url': 'https://cryptopanic.com/news/21069129/Saylors-Strategy-adds-3459-Bitcoin-now-holds-531644-BTC?mtm_campaign=API-OFA',
  'sumber': 'CryptoBriefing',
  'waktu': '2025-04-14T12:03:51Z',
  'mata_uang': 'BTC',
  'content': 'Saylor’s Strategy adds 3,459 Bitcoin, now holds 531,644 BTC'},
 {'judul': 'Saylor signals new Bitcoin buy after Strategy reports nearly $6 billion Q1 unrealized loss',
  'url': 'https://cryptopanic.com/news/21056879/Saylor-signals-new-Bitcoin-buy-after-Strategy-reports-nearly-6-billion-Q1-unrealized-loss?mtm_campaign=API-OFA',
  'sumber': 'CryptoBriefing',
  'waktu': '2025-04-13T14:44:50Z',
  'mata_uang': 'BTC',
  'content': 'Saylor signals new Bitcoin buy after Strategy reports nearly $6 billion Q1 unrealized loss'}]
```

In [27]:
```python
import nltk
from nltk.sentiment.vader import SentimentIntensityAnalyzer
import pandas as pd

nltk.download('vader_lexicon')

sia = SentimentIntensityAnalyzer()

all_articles = news_articles + news_data
df_news = pd.DataFrame(all_articles)
df_news['content'] = df_news['content'].astype(str)

def vader_sentiment(text):
    score = sia.polarity_scores(text)['compound']
    if score >= 0.05:
        return 'Positive'
    elif score <= -0.05:
        return 'Negative'
```

```
    else:
        return 'Neutral'

df_news['sentimen'] = df_news['content'].apply(vader_sentiment)

df_news[['title', 'sentimen']].head()
```

```
[nltk_data] Downloading package vader_lexicon to /root/nltk_data...
[nltk_data]   Package vader_lexicon is already up-to-date!
```

Out[27]:

	title	sentimen
0	Dogecoin Slumps 3%, Bitcoin Steady Around $85K...	Negative
1	Nomura's Laser Digital Denies Involvement in M...	Negative
2	Bitcoin Faces 'Cloud Resistance' at $85K, Neut...	Positive
3	XRP, SOL and ADA Flash Bullish Patterns as Tra...	Positive
4	Metaplanet Becomes 10th Largest Public Bitcoin...	Positive

In [28]:

```
sentiment_counts = df_news['sentimen'].value_counts()
dominant_sentiment = sentiment_counts.idxmax()
jumlah_dominan = sentiment_counts.max()
total_berita = sentiment_counts.sum()

print("News Sentiment Conclusion (VADER)")
print(f"Total news analyzed: {total_berita}")
print(f"Dominant sentiment: {dominant_sentiment} ({jumlah_dominan} news)")
print("\nComplete distribution:")
print(sentiment_counts)
```

```
News Sentiment Conclusion (VADER)
Total news analyzed: 37
Dominant sentiment: Positive (14 news)

Complete distribution:
sentimen
Positive    14
Negative    13
Neutral     10
Name: count, dtype: int64
```

Decision

In [29]:

```
prediction_sentiment = ''
if df_analyze.iloc[-1]['close'] > forecast_actual['Price'].mean():
  prediction_sentiment = 'Negative'
elif df_analyze.iloc[-1]['close'] < forecast_actual['Price'].mean():
  prediction_sentiment = 'Positive'
else:
  prediction_sentiment = 'Neutral'

def signal(prediction_sentiment, dominant_sentiment):
    if prediction_sentiment == "Positive":
        if dominant_sentiment == "Positive":
            return "BUY"
        elif dominant_sentiment == "Neutral":
            return "WAIT"
        else:
            return "CAUTION"
    elif prediction_sentiment == "Negative":
        if dominant_sentiment == "Negative":
            return "SELL"
        elif dominant_sentiment == "Positive":
            return "CAUTION"
        else:
            return "WAIT"
    else:
        return "HOLD"

trading_signal = signal(prediction_sentiment, dominant_sentiment)
```

In [30]:

```
from matplotlib.patches import FancyBboxPatch

color_map = {
    "BUY": "#27ae60",
    "SELL": "#c0392b",
    "WAIT": "#f39c12",
    "CAUTION": "#f1c40f",
    "HOLD": "#7f8c8d"
}
```

```python
message_map = {
    "BUY": "Time to buy!",
    "SELL": "Consider selling",
    "WAIT": "Wait for confirmation",
    "CAUTION": "Caution, the market is unstable",
    "HOLD": "Hold the position"
}


fig, ax = plt.subplots(figsize=(6, 3))
ax.set_xlim(0, 1)
ax.set_ylim(0, 1)
ax.axis('off')

box = FancyBboxPatch((0.05, 0.2), 0.9, 0.6,
                      boxstyle="round,pad=0.05",
                      linewidth=2,
                      facecolor=color_map.get(trading_signal, "#7f8c8d"),
                      edgecolor='black')
ax.add_patch(box)

ax.text(0.5, 0.6, f"Signal: {trading_signal}", fontsize=18, weight='bold',
        color='white', ha='center', va='center')

ax.text(0.5, 0.4, message_map.get(trading_signal, ""), fontsize=12,
        color='white', ha='center', va='center')

plt.title("Today Recommendations", fontsize=14)
plt.show()
```