DOUBLE BO, Shannon Li, Joshua Maddox (IP) Book and Ingraham, Shannon Li, Joshua Maddox (IP) Book ademola, David Ingraham, Shannon Li, Joshua Maddox (IP)

executive summary

- we wanted to be able to define our own events- not some pre-defined baseline identifiers out there
- we want to know exactly what it meant to be able to identify a price event- a black box calculation just won't do
- after identifying the event, we want to predict where the price will go- up or down



DATA COLLECTION AND PREPARATION PART 1: BRAIN STORMING

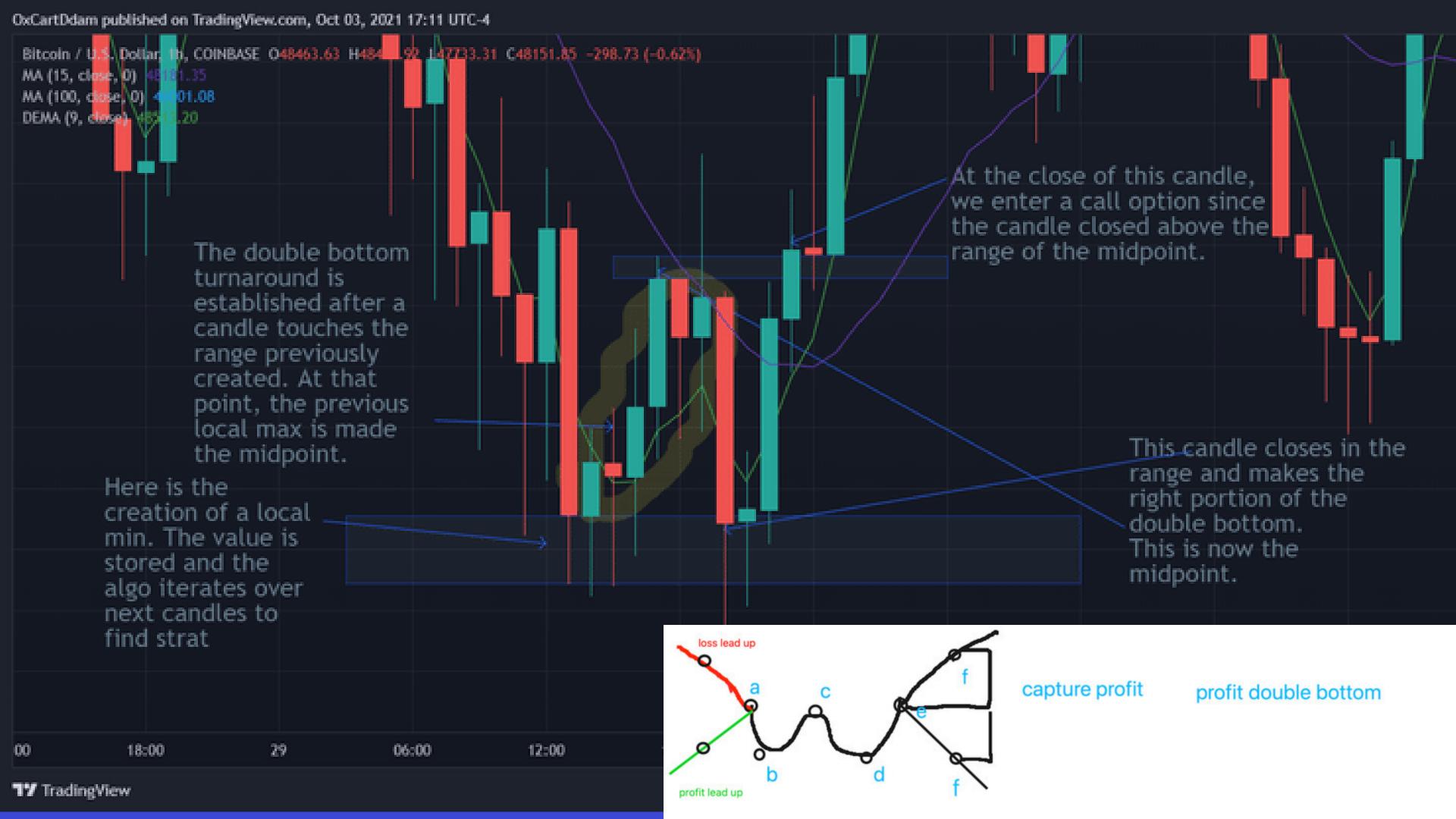
trading signals/events we were considering

- double bottoms
 - easiest to accomplish in 2 weeks
- head and shoulders
- double top
- inverse head and shoulders

visual and daxta references

- trading view
 - easily visually identify events
- yahoo finance
 - good starting point
- binance
 - collect large dataset easily
- coinbase







DATA COLLECTION AND PREPARATION PART 2: ETL

step1

what data points make up an event

step 2

how do we define each point with code logic

step 3

can we automate this for multiple events

		Date	Open	Low	High	Close	Volume	Max	Min	Α	В	С	D
	0	2017- 11-24	8138.99	8090.00	8734.78	8700.01	4292.623682	0.0	0.0	8212.00	8119.51	8205.92	8019.99
{0: [Timestamp('2017-11-19 00:00:00'), Timestamp('2017-11-20 00:00:00'), Timestamp('2017-11-21 00:00:00'), Timestamp('2017-11-22 00:00:00'), Timestamp('2017-11-24 00:00:00'), Timestamp('2018-03-27 00:00:00'), Timestamp('2018-03-27 00:00:00'), Timestamp('2018-03-29 00:00:00'), Timestamp('2018-03-30 00:00:00'), Timestamp('2018-03-31 00:00:00'), Timestamp('2018-04-01 00:00:00'), Timestamp('2018-08-04 00:00:00'), Timestamp('2018-08-07 00:00:00'), Timestamp('2018-08-09 00:00:00'), Timestamp('2018-08-09 00:00:00'), Timestamp('2018-08-16 00:00:00'), Timestamp('2018-09-26 00:00:00'), Timestamp('2018-09-28 00:00:00'), Timestamp('2018-09-29 00:00:00'), Timestamp('2018-09-29 00:00:00'), Timestamp('2018-10-02 00:00:00'), Timestamp('2019-01-23 00:00:00'), Timestamp('2019-01-28 00:00:00'), Timestamp('2019-01-28 00:00:00'), Timestamp('2019-02-01 00:00:00'), Timestamp('2019-02-20 00:00:00'), Timestamp('2019-02-21 00:00:00'), Timestamp('2019-02-22 00:00:00'), Timestamp('2019-02-23 00:00:00'), Timestamp('2019-02-24 00:00:00'), Timestamp('2019-03-24 00:00:00'), Timestamp('2019-03-19 00:00:00'), Timestamp('2019-03-24 00:00:00'), Timestamp('2019-03-20 00:00:00'),	1	2018- 04-01	6813.01	6765.00	7125.00	7056.00	32123.560072	0.0	0.0	7949.30	6840.23	6923.91	6813.01
	2	2018- 08-16	6316.00	6285.40	6585.00	6584.49	57851.610803	1.0	0.0	7024.19	6285.00	6529.79	6144.01
	3	2018- 10-04	6591.69	6543.08	6697.00	6635.65	16096.552392	1.0	0.0	6689.13	6596.38	6626.57	6510.00
	4	2019- 02-07	3398.40	3373.10	3733.58	3659.04	47968.058013	0.0	0.0	3569.62	3411.04	3504.77	3398.40
	5	2019- 03- 04	3716.10	3703.55	3877.10	3857.73	32962.536162	0.0	0.0	4117.76	3743.56	3827.92	3715.30
	6	2019- 03- 26	3948.77	3936.15	4048.00	4038.05	32364.555852	1.0	0.0	4043.04	3980.64	4006.01	3936.12
	7	2019- 07-29	9509.07	9402.00	9714.28	9574.21	32536.368834	0.0	0.0	9879.87	9476.52	9541.54	9507.64
	8	2019- 08-18	10306.17	10258.60	10930.00	10915.54	37243.319217	1.0	0.0	11549.97	10050.37	10331.54	10216.02
	9	2019- 09- 29	8043.04	7710.00	8337.26	8289.34	55865.487260	0.0	0.0	10415.01	8063.73	8198.81	8043.82
	10	2019- 11-03	9196.46	9115.84	9513.68	9393.35	45894.456277	1.0	0.0	9407.62	9140.85	9289.52	9194.71
	11	2019- 11-26	7154.75	6840.00	7655.00	7508.52	92452.873490	1.0	0.0	9289.52	7268.23	7311.57	6903.28
	12	2020-	8340.01	8293.66	8618.13	8615.00	31130.485164	0.0	0.0	8736.03	8404.52	8439.00	8340.58

APPROACH







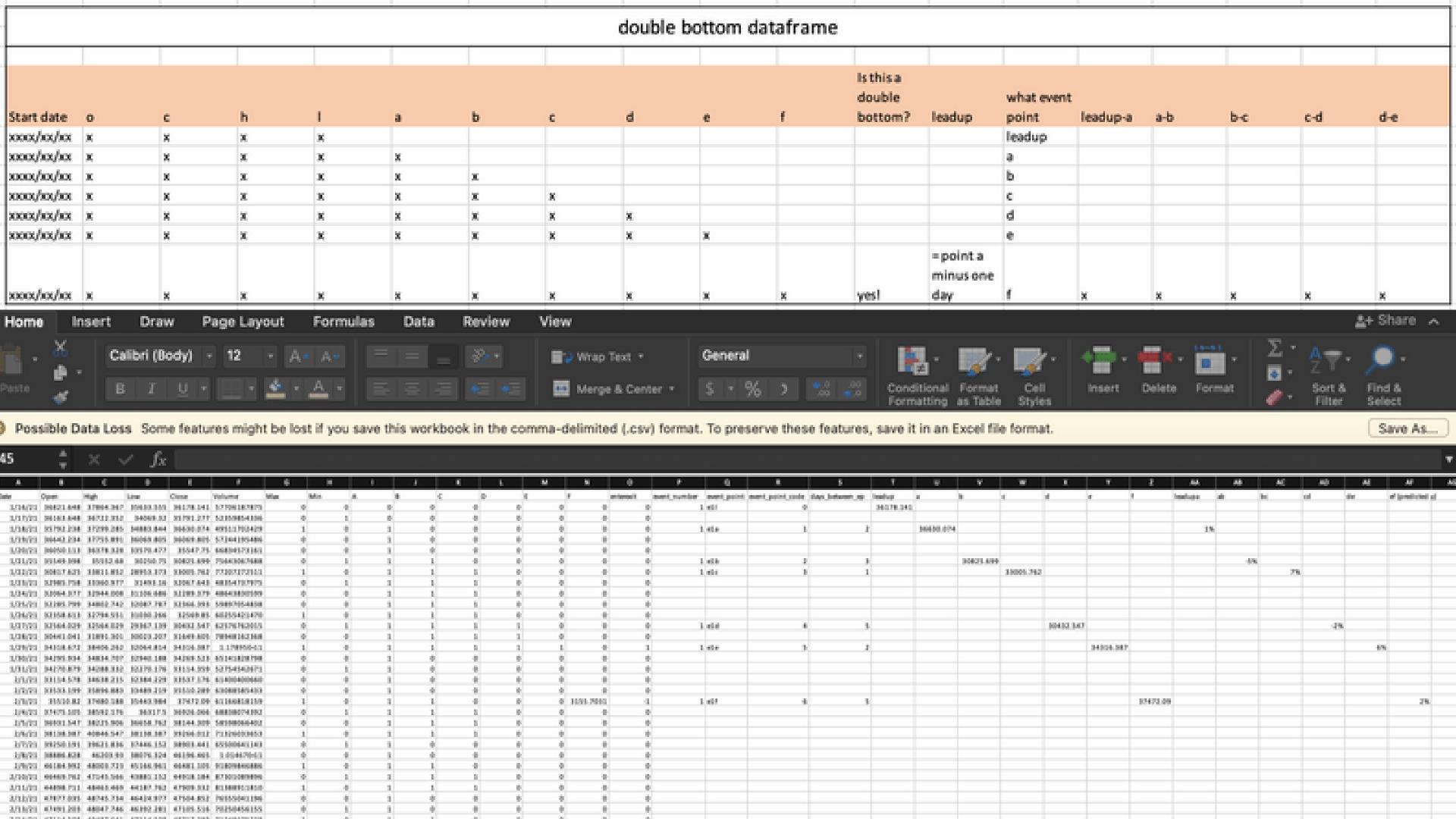


concept: event

actual: event

concept: NN dataframe

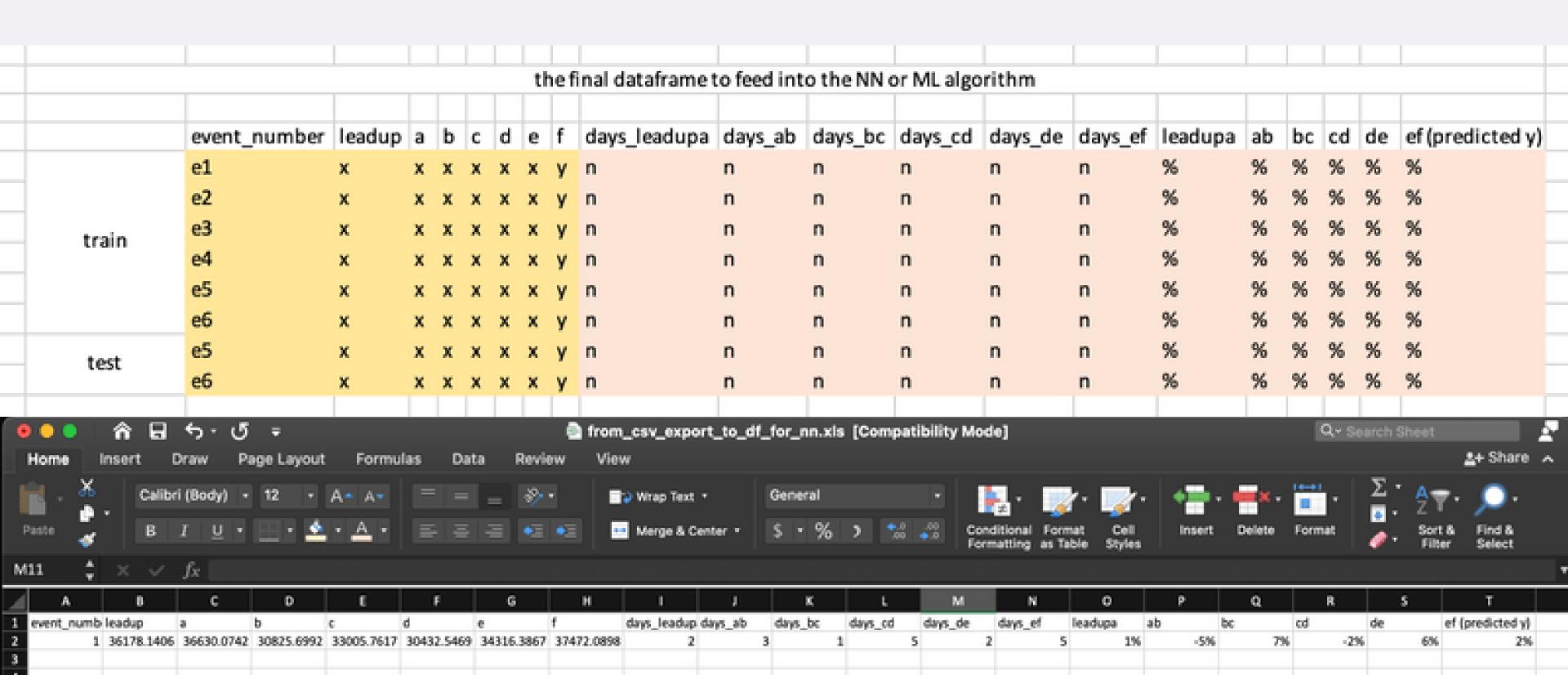
actual: NN datafram



Data pulled from event-identifying ML model

Engineered features to feed into our neural net

- From model #1:
 - 7 independent variables
- For model #2:
 - 19 features







identifying events visually

defining events in code

RESULTS/CONCLUSIONS PART 1: ML RESULTS FOR IDENTIFYING DOUBLE BOTTOM EVENTS

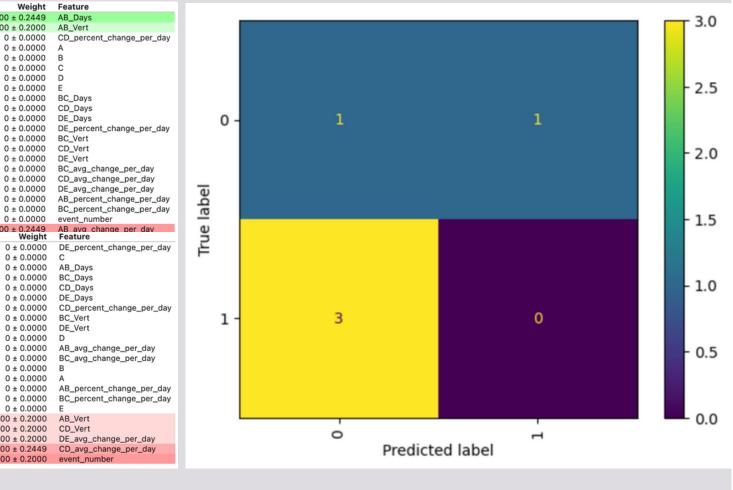


automating event identification

RESULTS/
CONCLUSION
PART 2:

NEURAL NET FOR PRICTING PRICE MOVEMENTS FOR TRADING ENTRY AND EXIT





```
pipeline103 = make_pipeline(
   ce.OrdinalEncoder(),
   XGBClassifier(booster= 'gbtree', n_estimators=30, max_depth=5,
               random_state=30,
               n_{jobs=-1}
y_test.tolist()
['0', '1', '1', '1', '0']
y_pred_103 = pipeline103.predict(X_test)
y_pred_103
array(['0', '0', '0', '0', '1'], dtype=object)
```

event point B to event point C

0.1500 ± 0.2449 AB_Day 0.0500 ± 0.2000 AB_Vert

 0 ± 0.0000

 0 ± 0.0000

0.00000

 0 ± 0.0000

 0 ± 0.0000 0 ± 0.0000

0.00000 ± 0.0000 DE_Days

 0 ± 0.0000

 0 ± 0.0000 0 ± 0.0000

0 + 0.0000

 0 ± 0.0000

 0 ± 0.0000

 0 ± 0.0000 -0.0500 ± 0.2000 AB_Vert -0.0500 ± 0.2000 CD_Vert

0 ± 0.0000 BC_Days

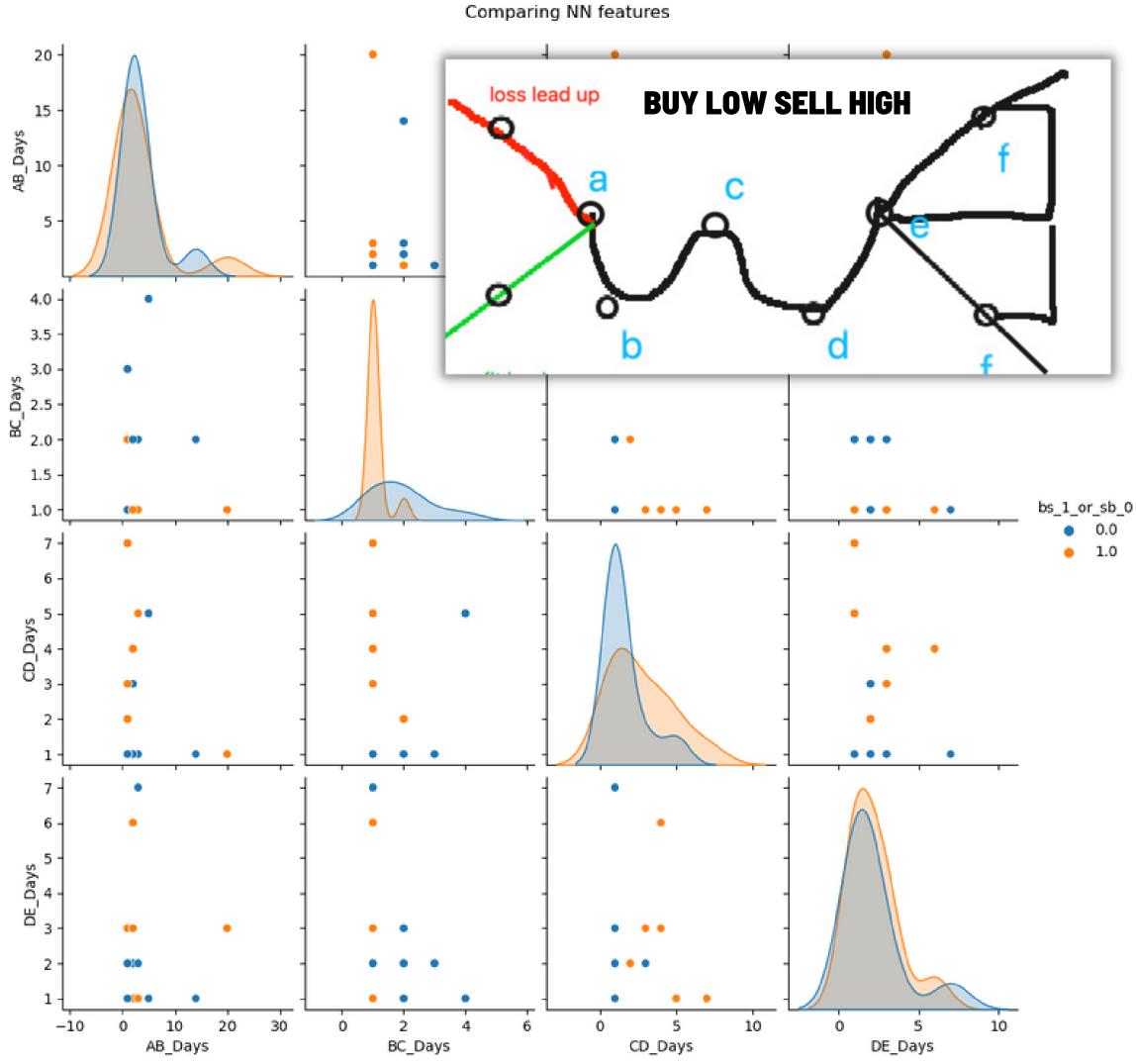
0 ± 0.0000 DE_Days 0 ± 0.0000

CD_Days

BC_Vert CD_Vert

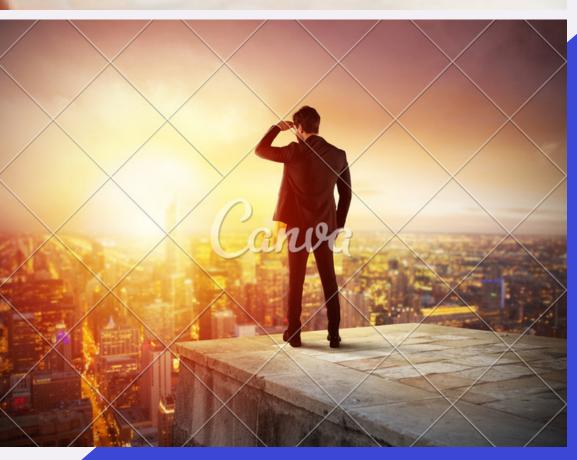
AB Davs BC_Days

- the lower the number of days, the more likely there is price increase, buy at e sell at f
- event point C to event point D
 - o the lower the number of days, the more likely price will decrease- sell at e and buy at f









NEXT STEPS; WHAT DID WE LEARN:

WHAT DO WE WISH WE COULD HAVE DONE:

WHAT COULD HAVE DONE BETTER

GITHUB:

https://github.com/bitcoin-candlestick-ML

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APPENDIX AND CREDITS