Crypto Wizards
Hunting for Edge

MACHINE LEARNING

APPLIED TO STOCK AND CRYPTO TRADING

SHAUN MCDONOGH

REALITY CHECK FOR MACHINE LEARNING IN FINANCE

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meme-arsenal.com

REALITY CHECK FOR PROGRAMMING

THEORY VS PRACTICE

Meme Generator

WHERE TO ASK QUESTIONS?

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Udemy

1x 0:30 / 2:58

Overview | Q&A | Notes | Announcements | Reviews | Learning tools

Search all course questions

All lectures | Sort by recommended | Filter questions

All questions in this course (390)

shift from "no adding" to "adding epsilon" ? 0 1

Hi Justin,I am lost in the last slide. I know it is elements in transition matrix.A(i,j) = p(j|i) = count(i->j)/...

YingHua · Lecture 5 · 5 years ago

Python 3x 0 5

Hi, Thanks for your courses, i used Python 3x and have error with translate function : return s.translat...

0 / 3 | 16min

45. Unsupervised o
3min

46. Generative vs. D
3min

47. HMM Classificat
Frost vs. Edgar Allar
11min

Section 8: Bonus Exa
Speech Tagging
0 / 2 | 11min

Section 9: Theano, Te
Machine Learning Ba
0 / 3 | 18min

Section 10: Setting U
Environment (FAQ by
0 / 2 | 38min

Section 11: Extra Help
Coding for Beginners
0 / 4 | 42min

Section 12: Effective
Strategies for Machin

WHERE TO ASK QUESTIONS?

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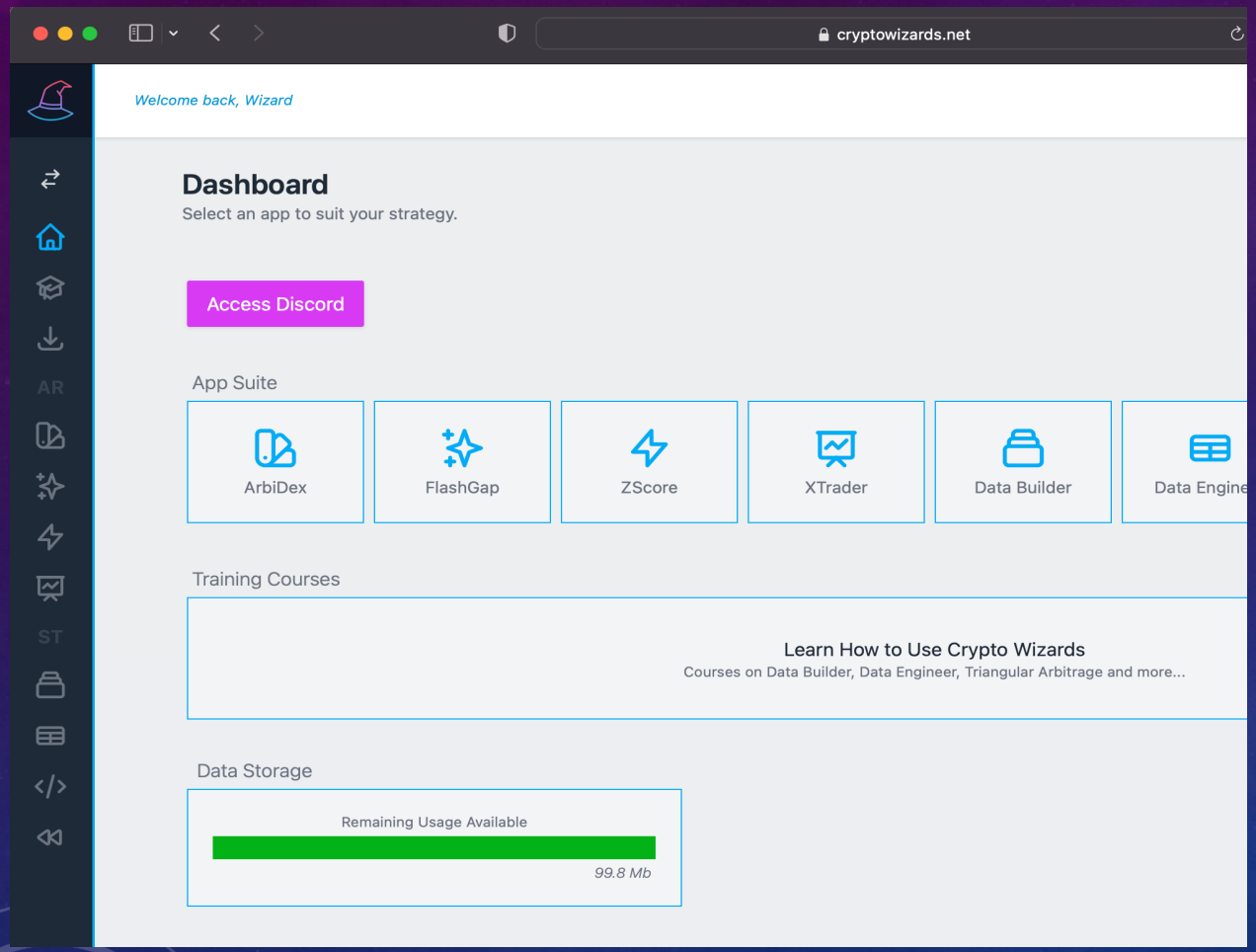
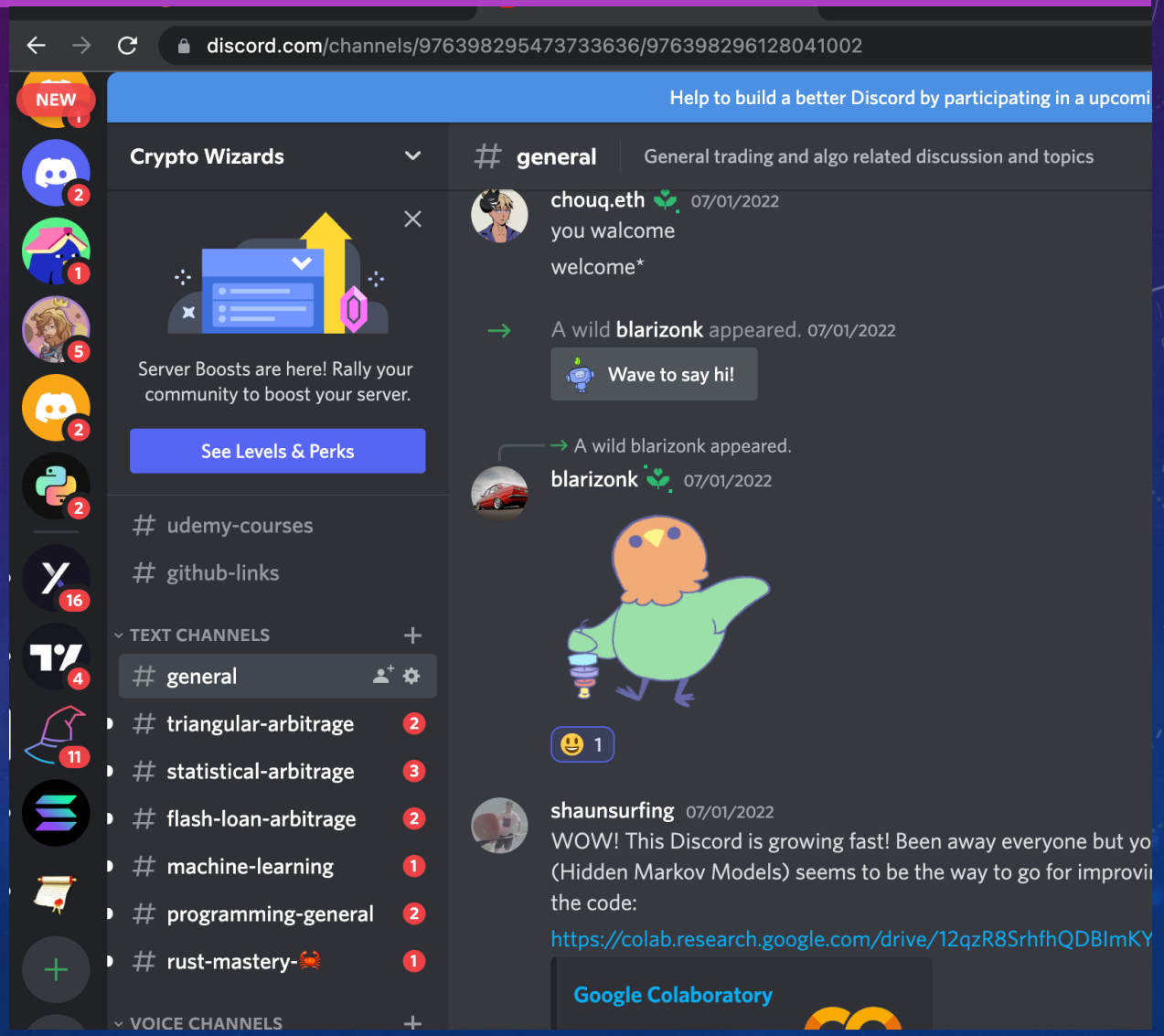
CryptoWizards.net Members





DISCORD

COURSE STRUCTURE

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PHASE 1	PHASE 2	PHASE 3	PHASE 4
PRIMERS	UNSUPERVISED LEARNING	SUPERVISED LEARNING	REINFORCEMENT LEARNING
Machine Learning General Overview	Unsupervised ML Theory	Supervised ML Theory	Reinforcement Learning (RL) Theory
Environment Setup and Retrieving Data	Hidden Markov Models – SPY	Data Preprocessing - BTC	Advanced RL Theory (Proximal Policy Gradient)
Python - 101	Backtesting with HMM – SPY	XGB Feature Selection - BTC	PPO – SINE WAVE
Pandas - 101	K-Means Clustering - Pairs Trading (ETF's)	XGB Binary Classification - BTC	PPO – STOCK TRADING (AAPL)
Backtesting - 101	Dimensionality Reduction - VIX (including Supervised ML)	Deep Learning Binary Classification	Conclusions and Next Steps
Feature Engineering - 101		Deep Learning with Sequential LSTM (Code Walkthrough)	
Market Efficiency Testing			

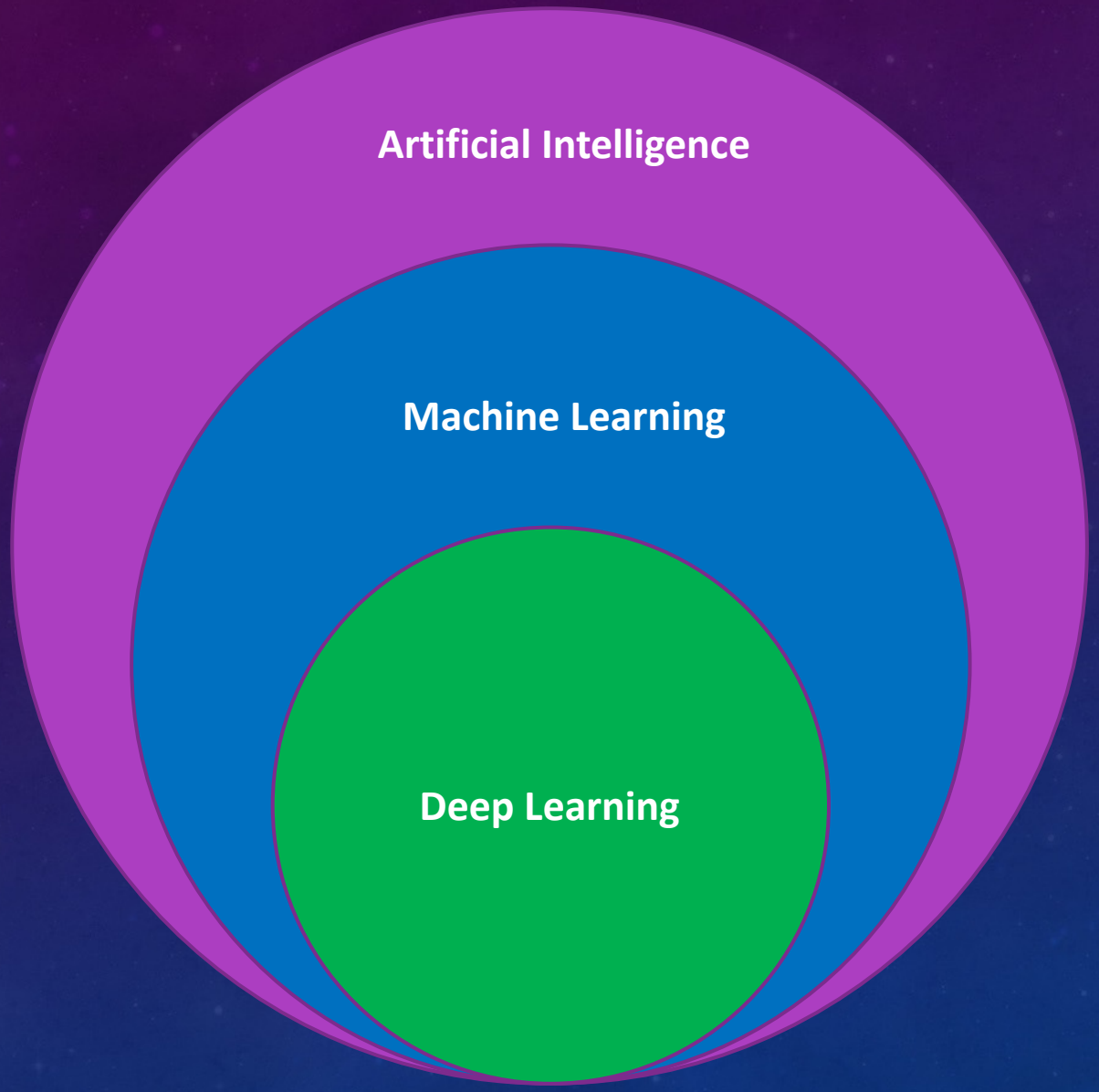
See APPENDIX for Trading Fundamentals

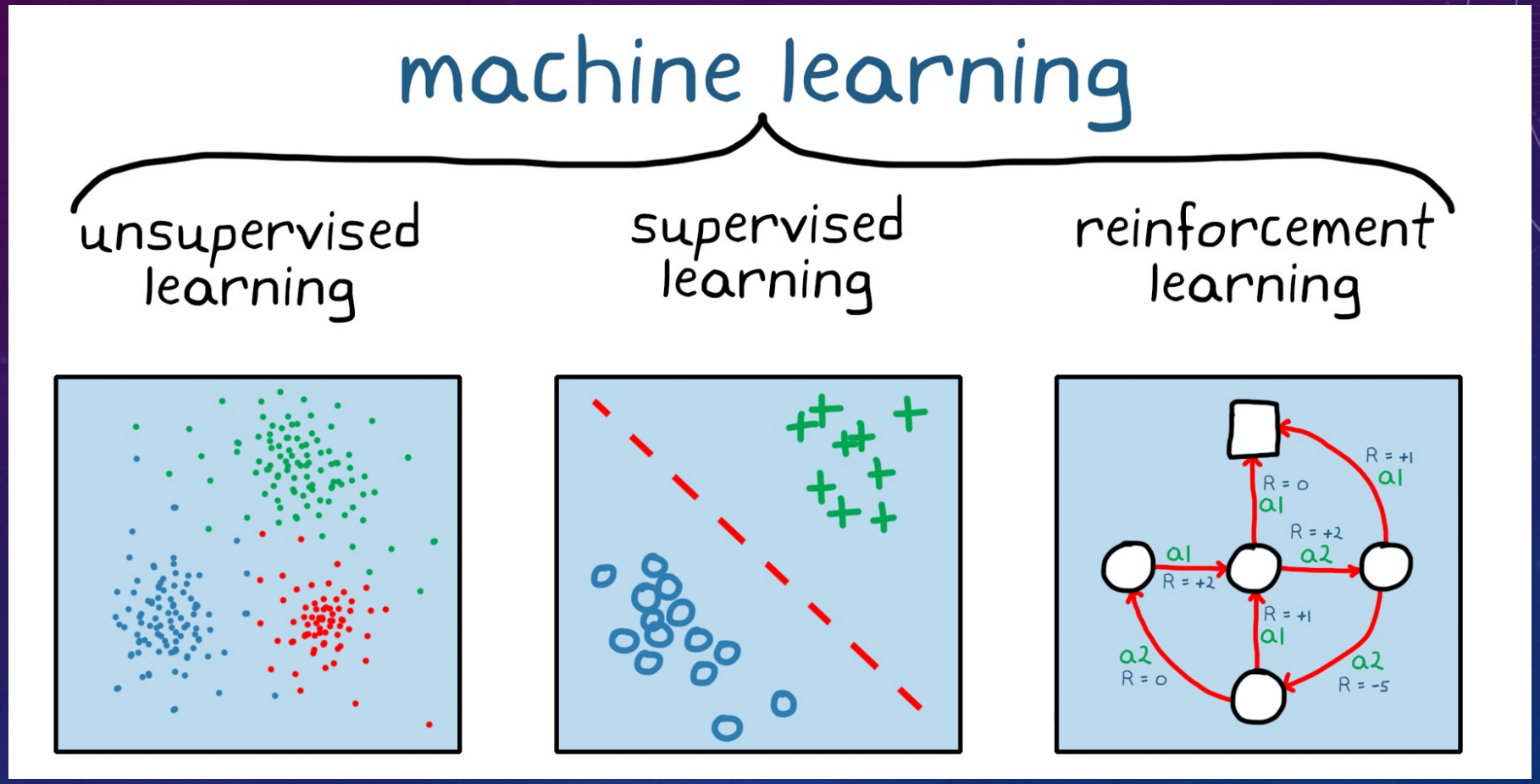
PRIMERS

PHASE 1

What is Machine Learning?

“Machine learning is a branch of artificial intelligence (AI) and computer science which focuses on the use of data and algorithms to imitate the way that humans learn, gradually improving its accuracy.” - IBM


Artificial Intelligence
Machine Learning
Deep Learning



https://www.mathworks.com/discovery/reinforcement-learning.html

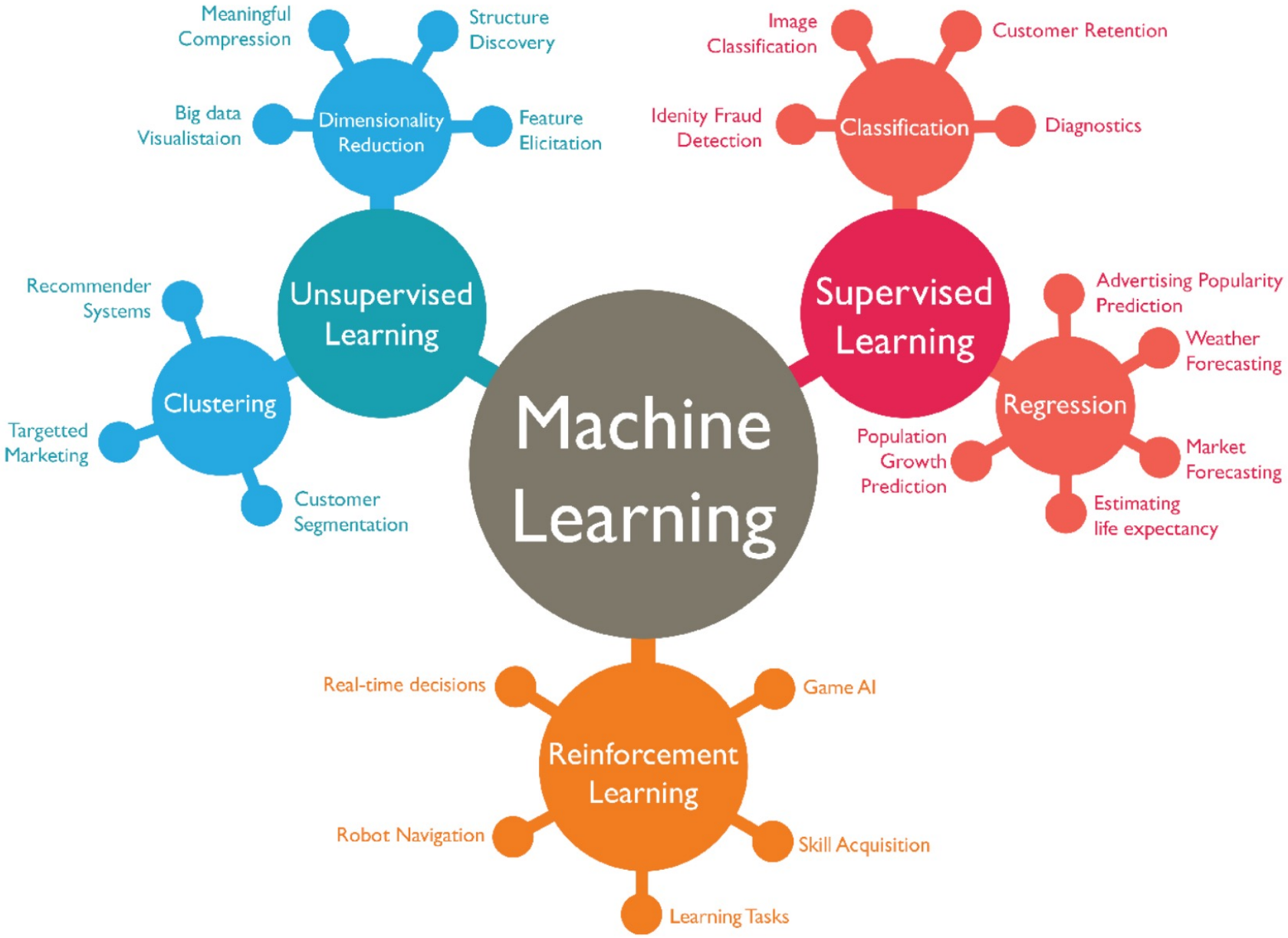


Image via Abdul Rahid

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https://www.wordstream.com/blog/ws/2017/07/28/machine-learning-applications

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$$f(x) \approx f(a) + f'(a)(x-a) + \frac{1}{2}f''(a)(x-a)^2$$

$$\mathcal{L}^{(t)} \simeq \sum_{i=1}^{n}[l(y_i, \hat{y}^{(t-1)}) + g_i f_t(\mathbf{x}_i) + \frac{1}{2}h_i f_t^2(\mathbf{x}_i)] + \Omega(f_t)$$

```
import xgboost
```

Machine Learning Pipeline

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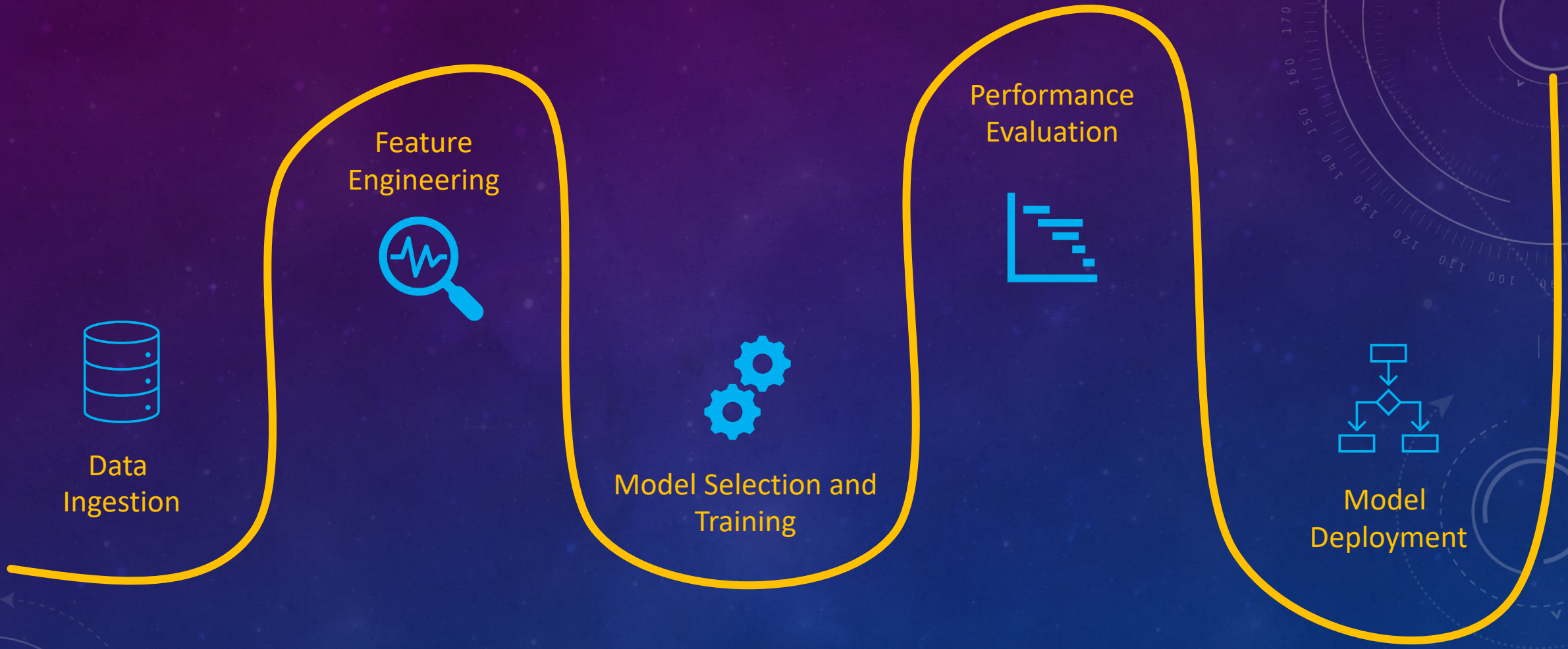
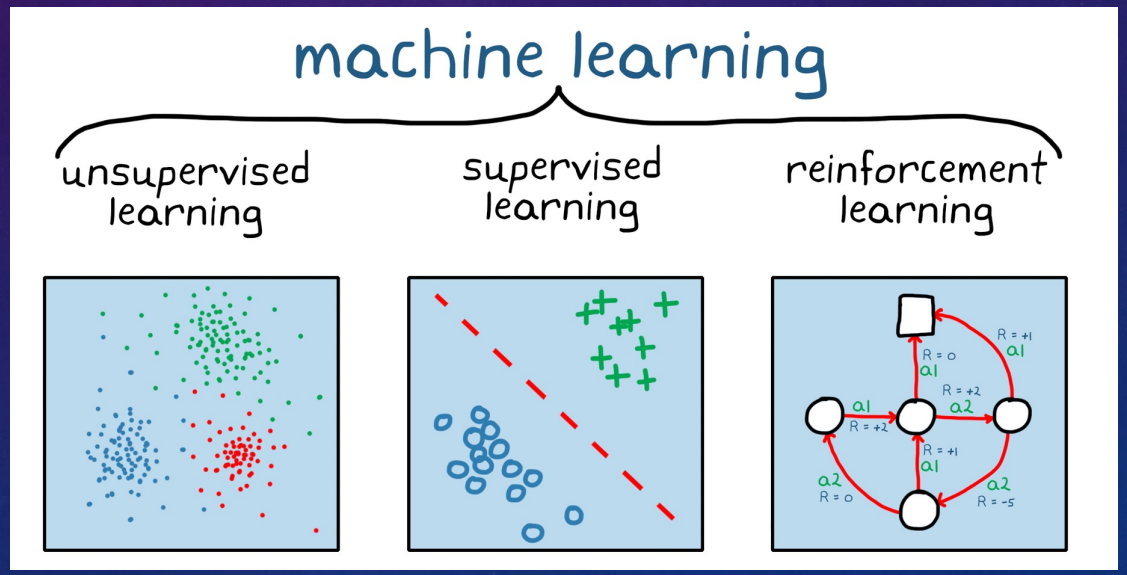


Google



https://www.mathworks.com/discovery/reinforcement-learning.html

Date	High	Low	Open	Close	Volume	Adj Close
2017-01-03	14.07	12.85	14.07	12.85	0	12.85
2017-01-04	12.80	11.63	12.78	11.85	0	11.85
2017-01-05	12.09	11.40	11.96	11.67	0	11.67
2017-01-06	11.74	10.98	11.70	11.32	0	11.32
2017-01-09	12.08	11.46	11.71	11.56	0	11.56

Date	High	Low	Open	Close	Adj Close	volume_mfi	volume_nvi	volatility_bbm	volatility_bbh	volatility_bbl	...	momentum_wr	momentum_ao	momentum_
2017-01-04	12.80	-0.094942	12.78	11.85	11.85	0.0	0.0	-0.038911	0.038911	-0.116732	...	-90.983594	0.0	
2017-01-05	12.09	-0.019776	11.96	11.67	11.67	0.0	0.0	-0.018354	-0.014123	-0.023329	...	-89.887624	0.0	

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Date	High	Low	Open	Close	Adj Close	volume_mfi	volume_nvi	volatility_bbm	volatility_bbh	volatility_bbl	...	momentum_wr	momentum_ao	momentum_
2017-01-04	12.80	-0.094942	12.78	11.85	11.85	0.0	0.0	-0.038911	0.038911	-0.116732	...	-90.983594	0.0	
2017-01-05	12.09	-0.019776	11.96	11.67	11.67	0.0	0.0	-0.018354	-0.014123	-0.023329	...	-89.887624	0.0	

TRAIN

FEATURE 1	FEATURE 2	FEATURE 3	TARGET
500	1.23	3.33	1
200	2.21	10.20	0
300	1.21	9.86	2
100	2.22	5.55	2
200	3.32	3.39	2
200	4.41	2.29	1
100	5.89	1.11	0

80%

TEST

FEATURE 1	FEATURE 2	FEATURE 3	TARGET
700	1.55	2.45	2
100	7.54	4.00	0
100	7.98	2.31	1

20%

TRAIN TEST SPLIT

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TRAIN

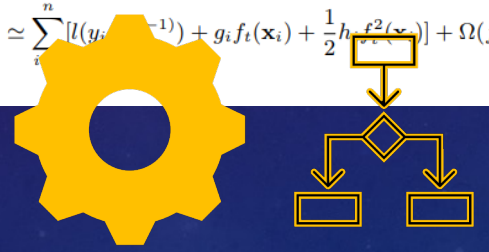
FEATURE 1	FEATURE 2	FEATURE 3	TARGET
500	1.23	3.33	1
200	2.21	10.20	0
300	1.21	9.86	2
100	2.22	5.55	2
200	3.32	3.39	2
200	4.41	2.29	1
100	5.89	1.11	0

71%

Accuracy

$$f(x) \approx f(a) + f'(a)(x-a) + \frac{1}{2}f''(a)(x-a)^2$$

$$\mathcal{L}^{(t)} \simeq \sum_{i}^{n} [l(y_i, \hat{y}_i^{(t-1)}) + g_i f_t(\mathbf{x}_i) + \frac{1}{2} h_i f_t^2(\mathbf{x}_i)] + \Omega(f_t)$$



Machine Learning Model

FEATURE 1	FEATURE 2	FEATURE 3	TARGET	PREDICTED
500	1.23	3.33	1	2
200	2.21	10.20	0	0
300	1.21	9.86	2	2
100	2.22	5.55	2	2
200	3.32	3.39	2	1
200	4.41	2.29	1	1
100	5.89	1.11	0	0

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TRAIN

FEATURE 1	FEATURE 2	FEATURE 3	TARGET	PREDICTED
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71%
Accuracy

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TRAIN

FEATURE 1	FEATURE 2	FEATURE 3	TARGET	PREDICTED
500	1.23	3.33	1	2
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200	4.41	2.29	1	1
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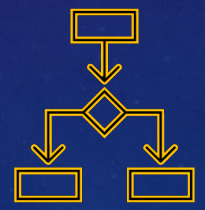
TEST

FEATURE 1	FEATURE 2	FEATURE 3	TARGET	PREDICTED
700	1.55	2.45	2	1
100	7.54	4.00	0	1
100	7.98	2.31	1	1

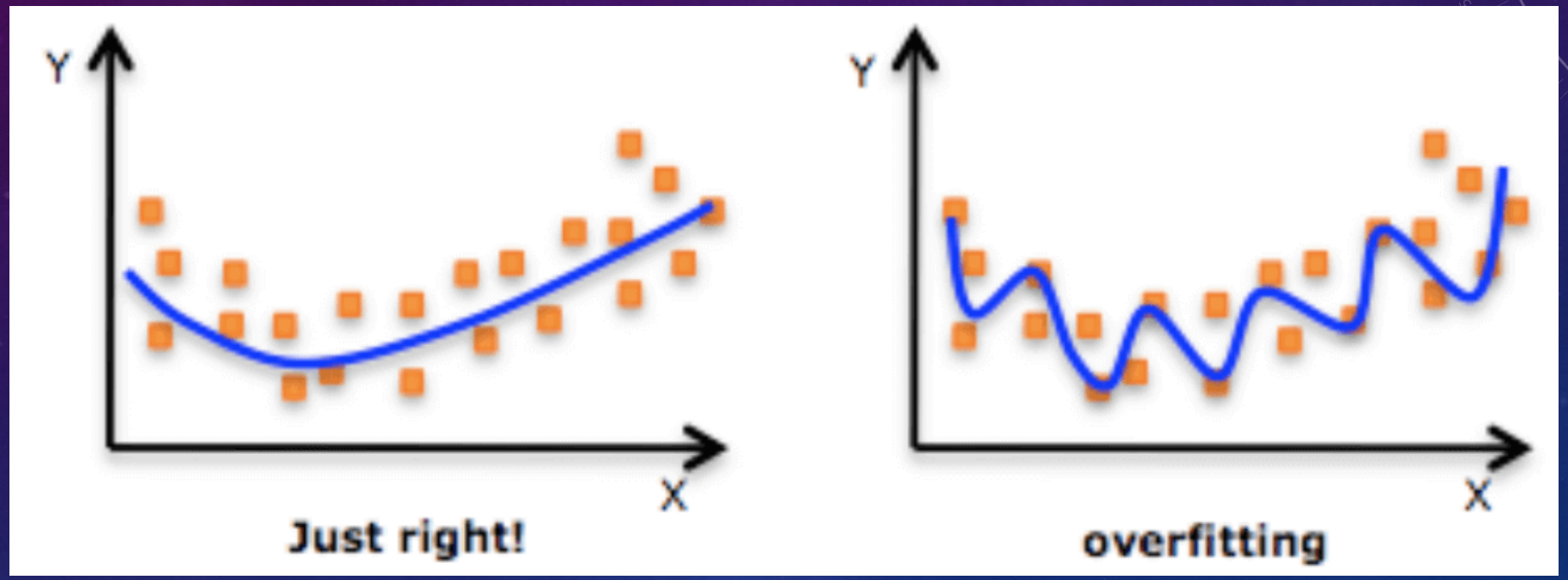
71%
Accuracy

52%
Accuracy

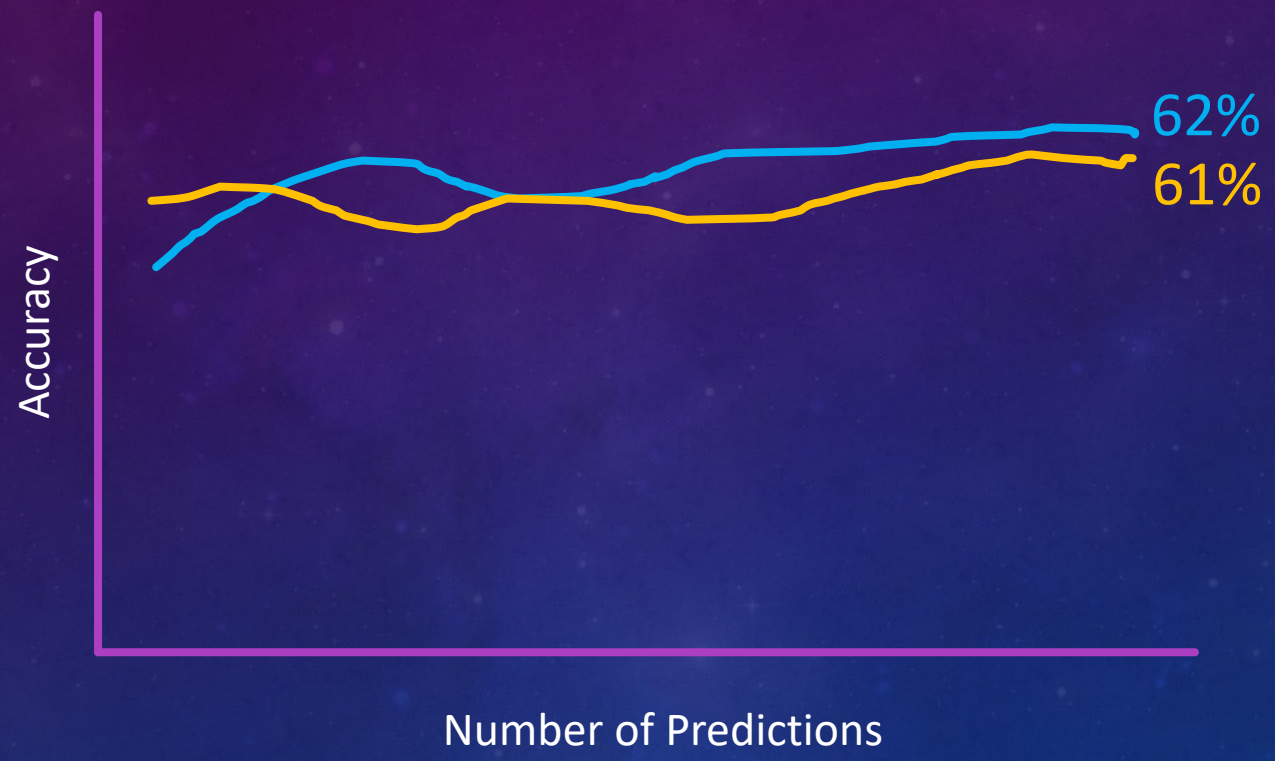


Trained
Machine Learning Model

Overfitting



https://www.datarobot.com/wiki/overfitting/


62%
61%
Accuracy
Number of Predictions

Data Ingestion

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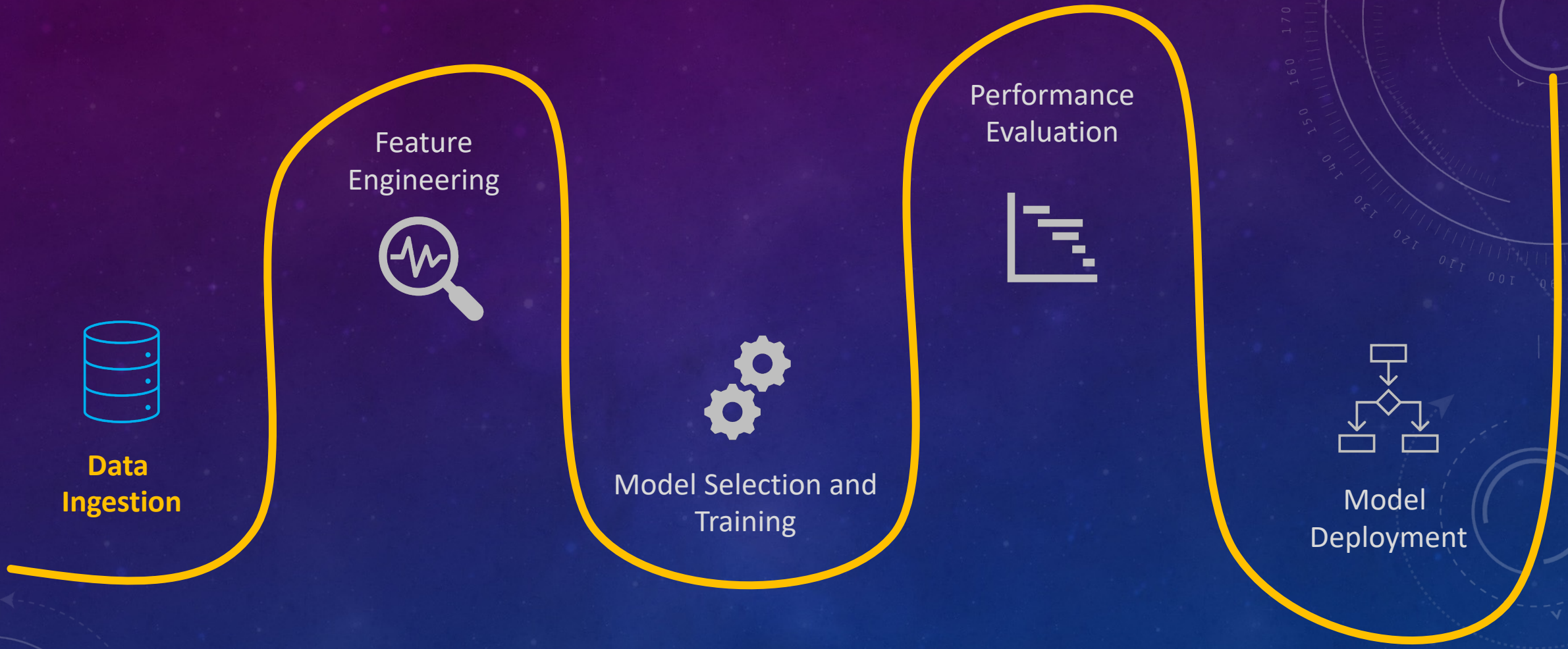

Where to Find Good Data for Trading

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Free

Yahoo Finance
Pandas DataReader
Google
Exchanges

Freemium

IEX
Alpha Vantage
Quandl
…many others

Paid

Financial Modelling Prep
Many Bespoke Data Providers
Crypto Wizards

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Be weary of:

- Missing/Incomplete Data
- Lack of Data
- Resource Credibility

What a Typical Dataset Looks Like

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	A	B	C	D	E	F	G	H	I	J	K	L
1	Datetime	Open	High	Low	Close	Adj_Close	Volume	Unadj_Volume	Change	Change_Percent	VWAP	Change_Over_Time
2	24/05/2012	20.566786	20.589287	20.043928	20.190001	17.288177	496230000	496230000	-0.37679	-1.832	20.27441	-0.01832
3	25/05/2012	20.163929	20.208929	19.945356	20.081785	17.195511	328507200	328507200	-0.08214	-0.407	20.07869	-0.00407
4	29/05/2012	20.389286	20.5	20.189644	20.438213	17.500711	380508800	380508800	0.04893	0.24	20.37595	0.0024
5	30/05/2012	20.328571	20.713928	20.234285	20.684643	17.711731	529429600	529429600	0.35607	1.752	20.54429	0.01752
6	31/05/2012	20.740713	20.767857	20.409286	20.633215	17.667685	491674400	491674400	-0.1075	-0.518	20.60345	-0.00518
7	01/06/2012	20.327143	20.451786	20.018572	20.035357	17.155756	520987600	520987600	-0.29179	-1.435	20.16857	-0.01435
8	04/06/2012	20.053572	20.267857	19.589287	20.153214	17.256674	556995600	556995600	0.09964	0.497	20.00345	0.00497
9	05/06/2012	20.045357	20.231071	19.940357	20.10107	17.21203	388214400	388214400	0.05571	0.278	20.09083	0.00278
10	06/06/2012	20.2775	20.494642	20.196428	20.409286	17.475945	401455600	401455600	0.13179	0.65	20.36679	0.0065
11	07/06/2012	20.6175	20.61857	20.375	20.418571	17.483896	379766800	379766800	-0.19893	-0.965	20.47071	-0.00965
12	08/06/2012	20.414286	20.735001	20.321428	20.725714	17.746887	347516400	347516400	0.31143	1.526	20.59405	0.01526
13	11/06/2012	20.99	21.017857	20.379642	20.39893	17.467077	591264800	591264800	-0.59107	-2.816	20.59881	-0.02816
14	12/06/2012	20.51643	20.593571	20.239286	20.577143	17.619677	435380400	435380400	0.06071	0.296	20.47	0.00296
15	13/06/2012	20.518572	20.66	20.370714	20.434286	17.497351	293580000	293580000	-0.08429	-0.411	20.48833	-0.00411
16	14/06/2012	20.401428	20.482143	20.259287	20.411785	17.478086	345573200	345573200	0.01036	0.051	20.38441	0.00051
17	15/06/2012	20.392857	20.522142	20.34107	20.504642	17.557592	335255200	335255200	0.11179	0.548	20.45595	0.00548
18	18/06/2012	20.39143	20.996071	20.370358	20.920713	17.913868	440412000	440412000	0.52928	2.596	20.76238	0.02596
19	19/06/2012	20.835714	21.071428	20.825001	20.97893	17.96372	361404400	361404400	0.14322	0.687	20.95845	0.00687
20	20/06/2012	21.0075	21.044643	20.742857	20.919287	17.912647	358943200	358943200	-0.08821	-0.42	20.90226	-0.0042
21	21/06/2012	20.908571	21.007856	20.622856	20.631071	17.665852	326351200	326351200	-0.2775	-1.327	20.75393	-0.01327
22	22/06/2012	20.68	20.7925	20.550714	20.789286	17.801325	284471600	284471600	0.10929	0.528	20.71083	0.00528
23	25/06/2012	20.617857	20.707144	20.370358	20.384644	17.454844	304382400	304382400	-0.23321	-1.131	20.48738	-0.01131
24	26/06/2012	20.404642	20.5175	20.261786	20.429644	17.49337	276536400	276536400	0.025	0.123	20.40298	0.00123
25	27/06/2012	20.535713	20.597857	20.425714	20.517857	17.568914	202997200	202997200	-0.01786	-0.087	20.51381	-0.00087
26	28/06/2012	20.416786	20.5	20.200357	20.323214	17.402235	282836400	282836400	-0.09357	-0.458	20.34119	-0.00458
27	29/06/2012	20.642857	20.857143	20.508928	20.857143	17.859436	421500800	421500800	0.21429	1.038	20.74107	0.01038
28	02/07/2012	20.883215	21.195356	20.842857	21.161428	18.11998	400092000	400092000	0.27821	1.332	21.06655	0.01332
29	03/07/2012	21.245714	21.428572	21.214287	21.407499	18.330688	241712800	241712800	0.16179	0.762	21.35012	0.00762
30	05/07/2012	21.44857	21.940714	21.416071	21.783571	18.652714	484383200	484383200	0.335	1.562	21.71345	0.01562
31	06/07/2012	21.681786	21.73	21.485001	21.638571	18.528547	418930400	418930400	-0.04322	-0.199	21.61786	-0.00199
32	09/07/2012	21.617857	21.924999	21.575357	21.924643	18.773504	379405600	379405600	0.30679	1.419	21.80833	0.01419
33	10/07/2012	22.070356	22.138214	21.618214	21.721786	18.599804	511957600	511957600	-0.34857	-1.579	21.82607	-0.01579
34	11/07/2012	21.647142	21.702143	21.329287	21.586786	18.484205	469322000	469322000	-0.06036	-0.279	21.53941	-0.00279
35	12/07/2012	21.437143	21.5525	21.167143	21.389286	18.315094	428041600	428041600	-0.04786	-0.223	21.36964	-0.00223
36	13/07/2012	21.53393	21.685356	21.428572	21.606071	18.500723	311427200	311427200	0.07214	0.335	21.57333	0.00335

Feature Engineering

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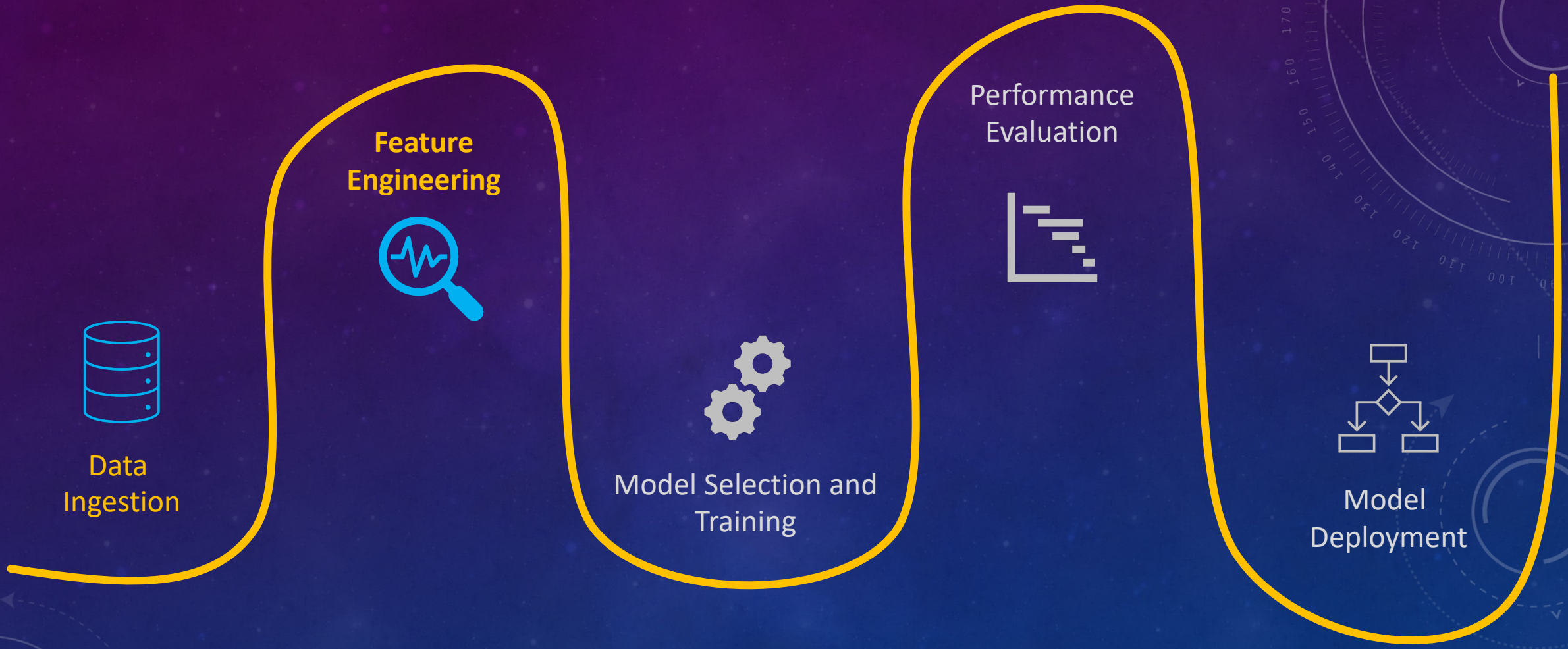

FEATURE ENGINEERING – VARIABLE TYPES AND TASKS

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- Numerical
- Categorical
- Datetime
- Mixed

- Outliers
- Stationary
- Complete Data

- Categorical
- Numerical
- Feature Scaled

FEATURE ENGINEERING – VARIABLE TYPES AND TASKS

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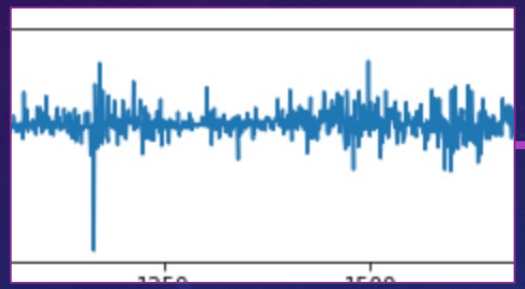


- Categorical

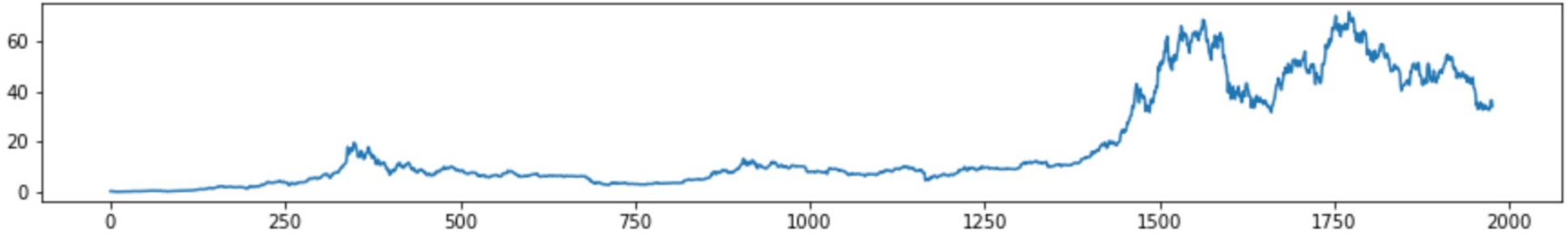
pt_house	pt_other	pt_terrace	pt_townhouse	pt_villa
1	0	0	0	0
1	0	0	0	0
1	0	0	0	0

- Numerical

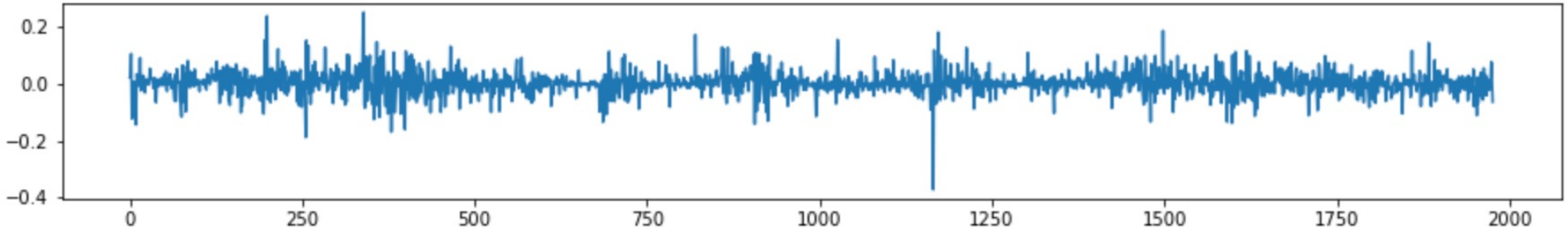
	PC_0	PC_1	PC_2	PC_3	PC
0	-4.663399	-0.247211	-2.611970	0.757772	1.069
1	-1.816759	4.547170	-1.009873	0.755642	0.711
2	2.026221	-4.735525	-0.753187	0.901963	-1.686
3	-4.800988	0.887544	2.454545	-0.724577	2.042

- Feature Scaled

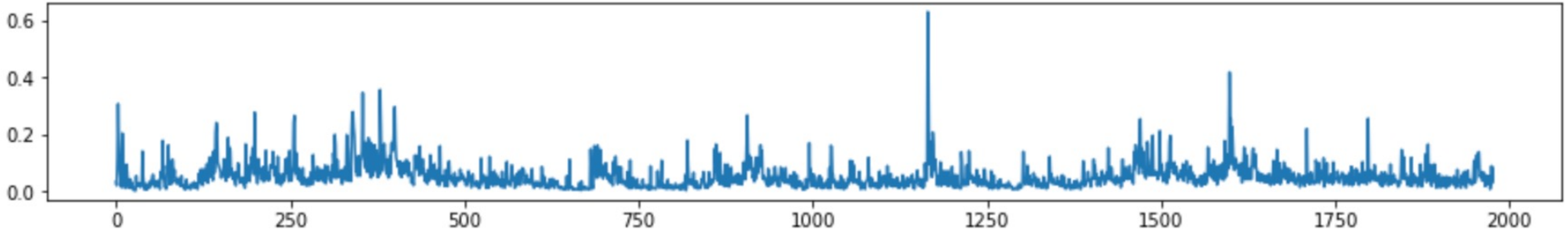
```
-1.26409996, -1.13423463, -0.6337293
 0.01966657,  0.02740599,  0.1310101
-1.29635361, -1.17494635, -0.5866151
-0.93975017, -0.15742203, -0.0699439
```




```python
# Benchmark Returns Profile
fig = plt.figure(figsize = (15,2))
plt.plot(df["Returns"].values)
plt.show()
```




```python
# Benchmark Range Profile
fig = plt.figure(figsize = (15,2))
plt.plot(df["Range"].values)
plt.show()
```



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STATIONARITY

Model Selection and Training

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Data Ingestion

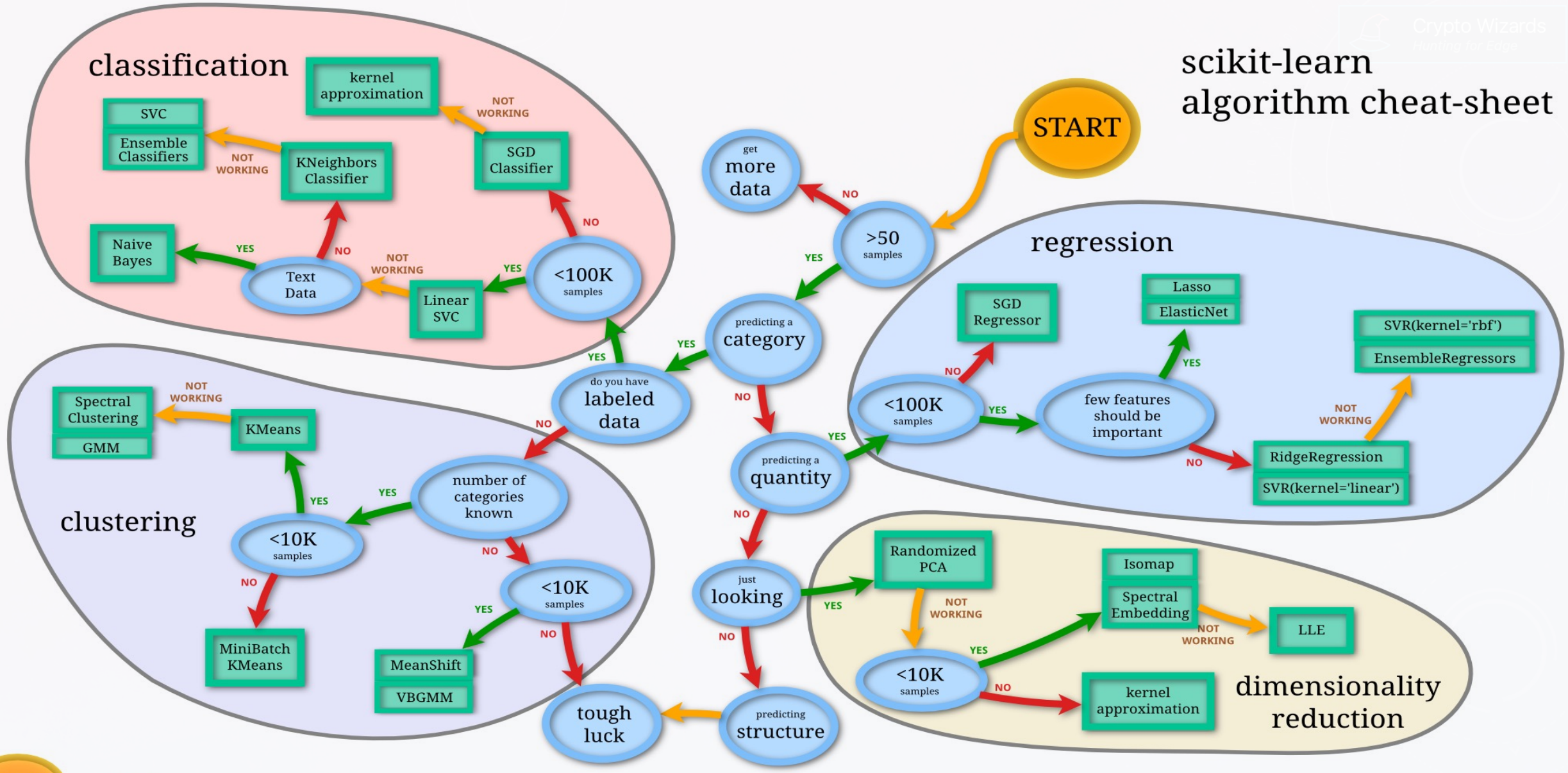
Feature Engineering

Model Selection and Training

Performance Evaluation

Model Deployment

scikit-learn algorithm cheat-sheet



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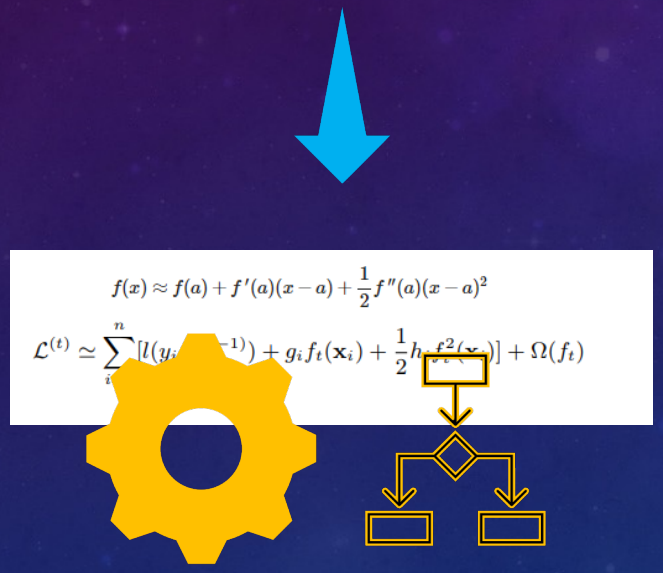
Dimensionality Reduction	Unsupervised	Principle Component Analysis (PCA)
Clustering	Unsupervised	K-Means Clustering Hidden Markov Model
Classification	Supervised	XGBOOST, Random Forest Classifier
Regression	Supervised	Random Forest Regressor
Reinforcement Learning	Reinforcement, Deep Learning	Proximal Policy Gradient

TRAIN

FEATURE 1	FEATURE 2	FEATURE 3	TARGET
500	1.23	3.33	1
200	2.21	10.20	0
300	1.21	9.86	2
100	2.22	5.55	2
200	3.32	3.39	2
200	4.41	2.29	1
100	5.89	1.11	0



Machine Learning Model

```
model = XGBClassifier (params)
model.fit(X_train, y_train)
model.predict(X_train)
```

Performance Evaluation

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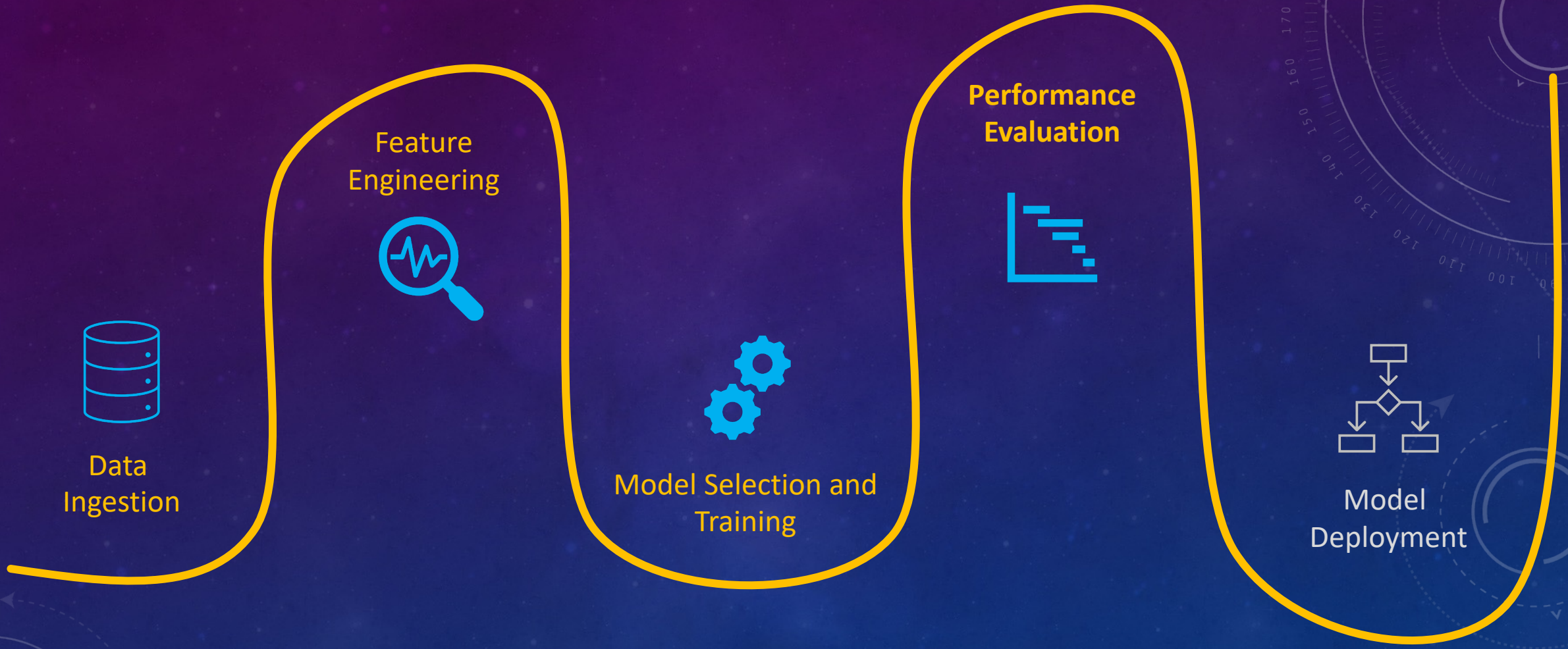

PERFORMANCE EVALUATION
Supervised Learning - Classification vs Regression

Binary Classification

Actual (True)	Predicted
1	1
0	0
1	1
1	0
0	1
1	0
0	0

Multi-class Classification

Actual (True)	Predicted
1	1
2	2
2	1
0	0
1	1
1	1
3	0

Regression

Actual (True)	Predicted
598,098	550,988
261,923	256,010
345,231	250,877
109,992	234,008
1,620,908	1,201,200
212,985	150,911
311,347	314,200

Classification is categorical, whilst regression is continuous.

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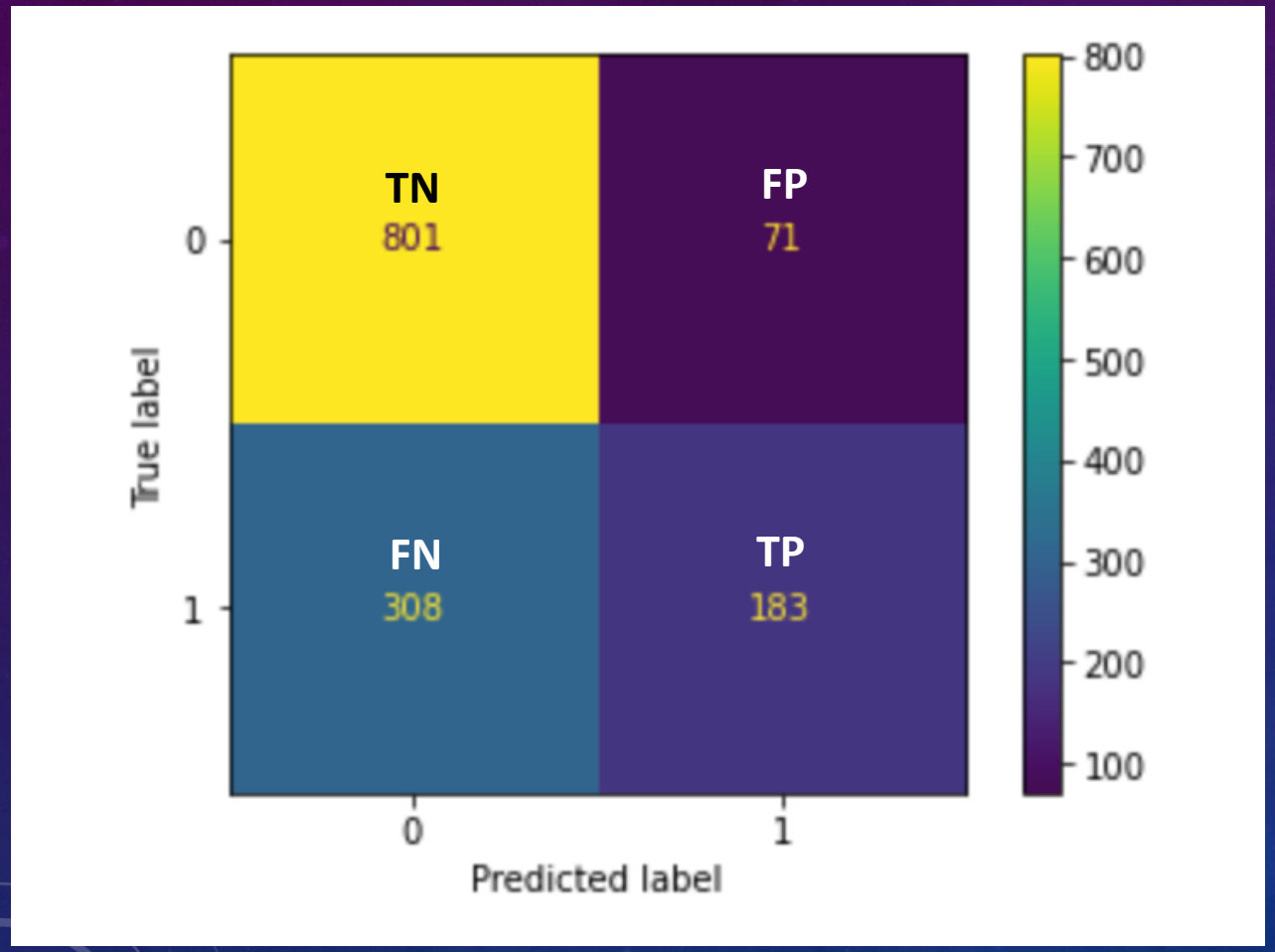
PERFORMANCE EVALUATION
Binary (and Multi-class) Classification – Confusion Matrix



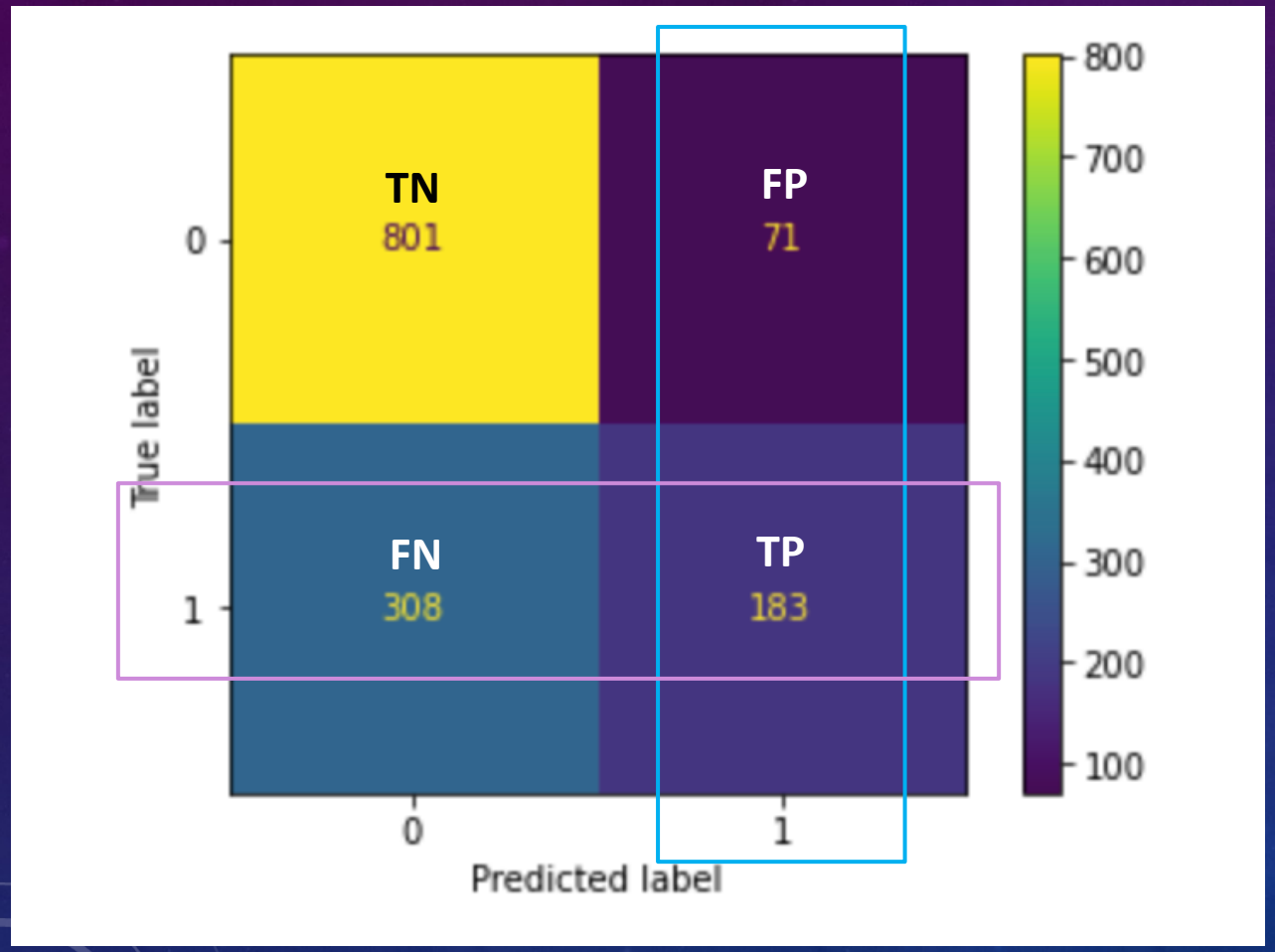
TN = TRUE NEGATIVE

FP = FALSE POSITIVE

FN = FALSE NEGATIVE

TP = TRUE POSITIVE

PERFORMANCE EVALUATION
* Binary Classification – Confusion Matrix



Accuracy = Total Correct / Total Predictions

Precision = TP / (TP + FP)

Recall = TP / (TP + FN)

F1 Score = 2 x ((Precision x Recall) / (Precision + Recall))

https://towardsdatascience.com/the-f1-score-bec2bbc38aa6

PERFORMANCE EVALUATION
* Binary Classification – Summary Report

	precision	recall	f1-score	support
0.0	0.67	0.88	0.76	357
1.0	0.62	0.31	0.41	228
accuracy			0.66	585
macro avg	0.65	0.59	0.59	585
weighted avg	0.65	0.66	0.62	585

We literally tell our XGBOOST model, to optimize for Precision and make this it's priority.

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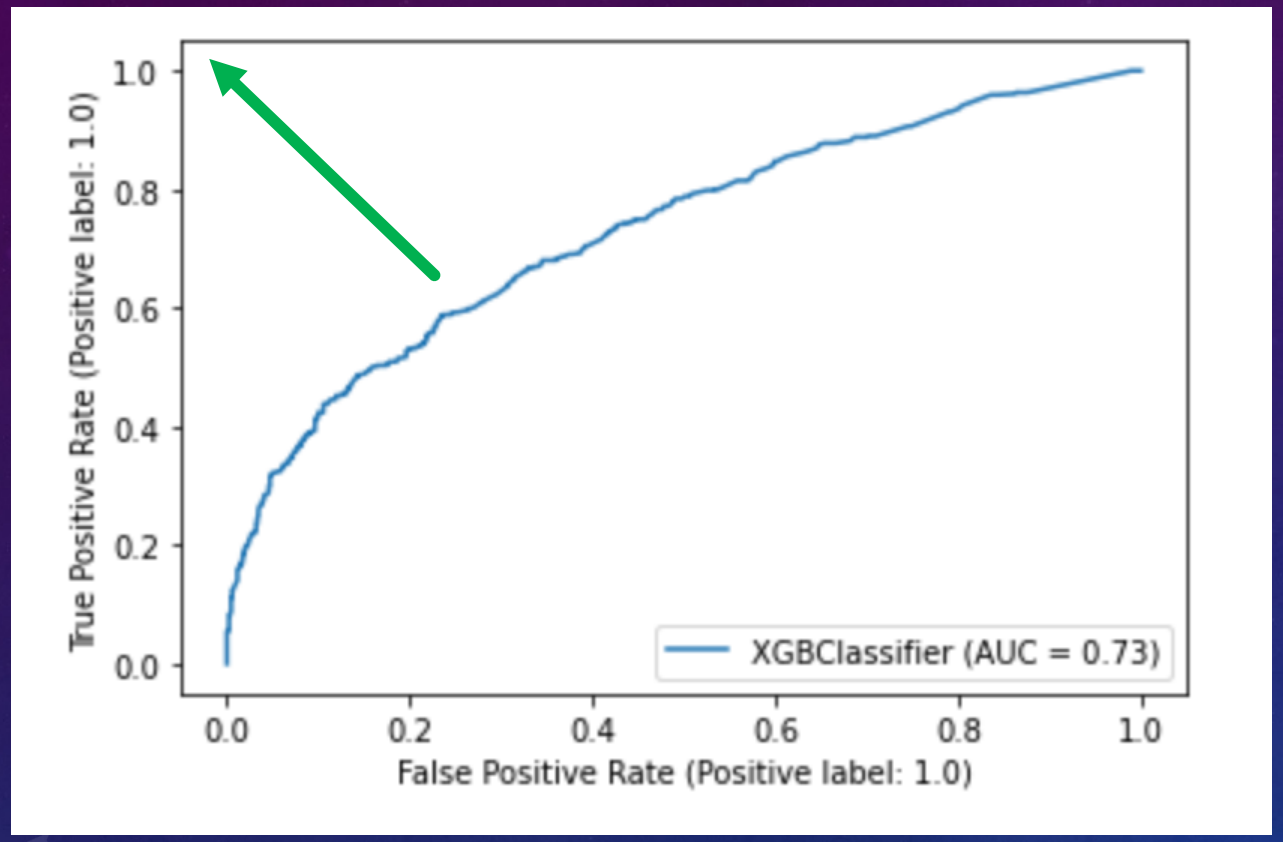
PERFORMANCE EVALUATION
* Binary Classification – ROC Curve



ROC = Receiver Operating Characteristic
Shows the False Positives and True Positives at different discrimination thresholds. This is usually set to 50% and is adjusted on this chart to show sensitivity to false positives for example.

AUC = Area Under the Curve
The greater the AUC the better. If predicting 100% items incorrectly, AUC will be 0. Predicting all correctly would provide an AUC of 1.

Overfitting: ROC is Useful as an overfitting check when comparing Train vs Test. If Test looks very poor, i.e. not moving towards the top left corner. Our model is likely overfit.

Google ML Course Example

PERFORMANCE EVALUATION
Regression

MAE = Mean Absolute Error

The average of all absolute errors.

MAPE = Mean Absolute Percentage Error

MAE percentage equivalent.

MSE = Mean Squared Error

Like MAE, although squares the difference before summing the results. Helpful if there are outliers in the data, as certain errors grow quadratically with MSE.

RMSE = Root Mean Squared Error

The square root of MSE.

https://www.dataquest.io/blog/understanding-regression-error-metrics

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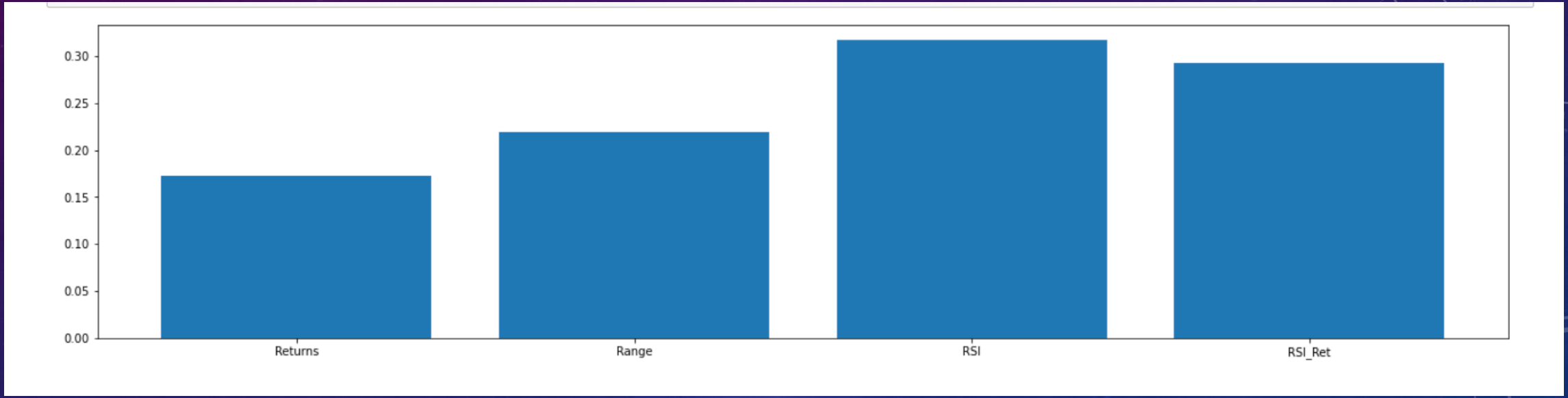
PERFORMANCE EVALUATION
Feature Importance (Classification and Regression)



Model Deployment

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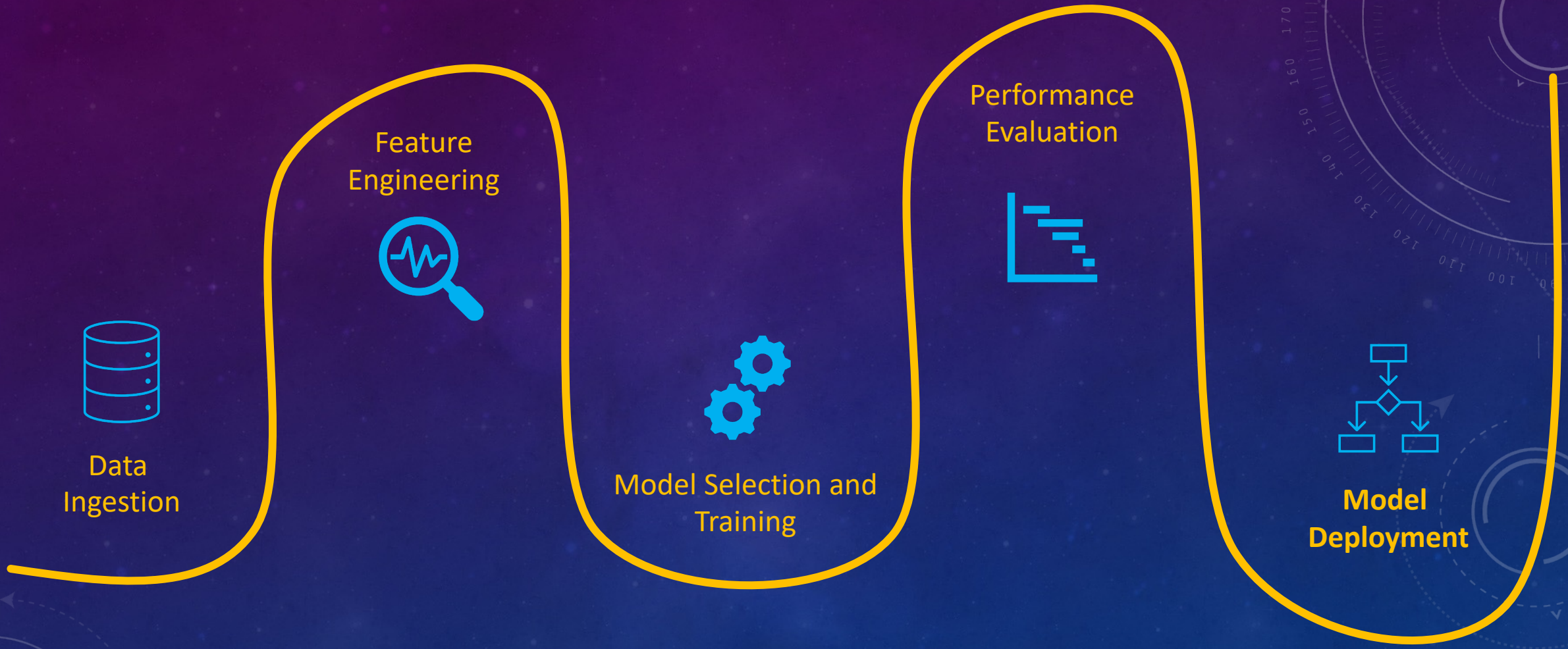

MODEL DEPLOYMENT

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Save model to local file and run your code automatically in Python with a while True loop:

```
import time
while True:
    <Execute code>
    time.sleep(300)
```

...or...

Deploy model to a web host and execute script via a cron job or always on task.

Deployment will not be covered as part of this course and will be covered as a stand-alone course due to the steps and different type of nature to this course which is involved.

Recommended technologies for running Python in the cloud are Heroku or AWS and FastAPI.

UNSUPERVISED LEARNING

PHASE 2

WHAT IS UNSUPERVISED LEARNING?

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"Unsupervised learning, also known as unsupervised machine learning, uses machine learning algorithms to analyze and cluster unlabeled datasets. These algorithms discover hidden patterns or data groupings without the need for human intervention. Its ability to discover similarities and differences in information make it the ideal solution for exploratory data analysis, cross-selling strategies, customer segmentation, and image recognition." - IBM

https://www.ibm.com/cloud/learn/unsupervised-learning

COURSE FOCUS

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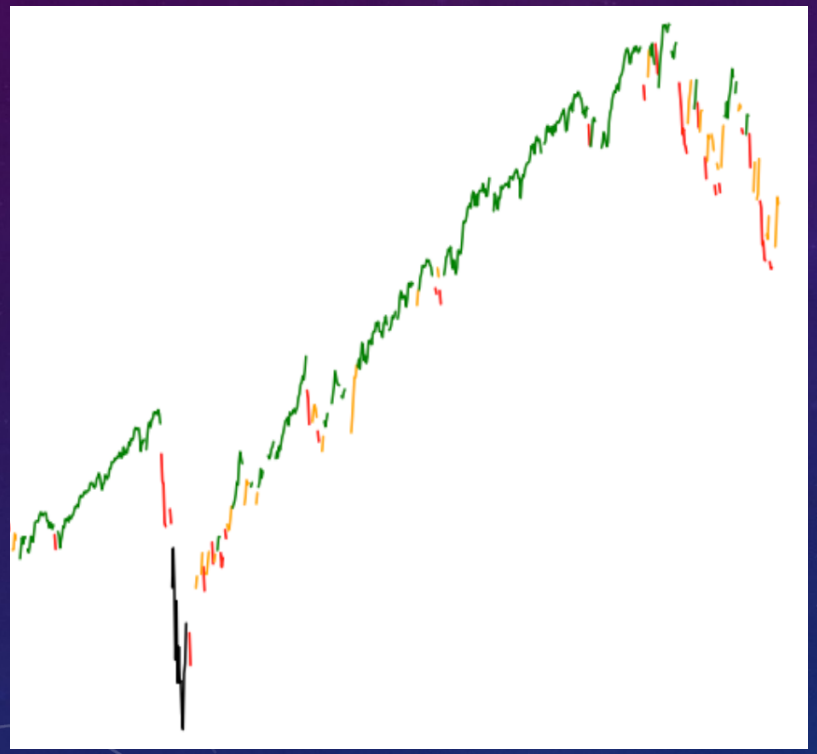
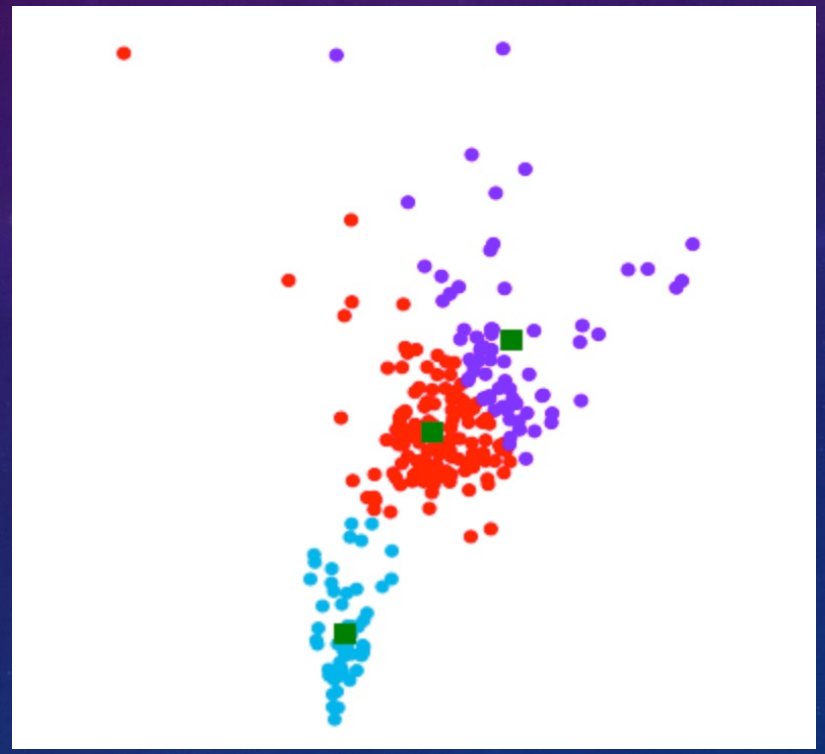
Probabilistic Clustering

Hidden Markov Model (HMM)



Exclusive Clustering

K-Means Clustering



Dimensionality Reduction

Principle Component Analysis

Close	Adj Close	volume_mfi	volume_nvi	volatility_bbm	volatility_bbh
11.85	11.85	0.0	0.0	-0.038911	0.038911
11.67	11.67	0.0	0.0	-0.018354	-0.014123

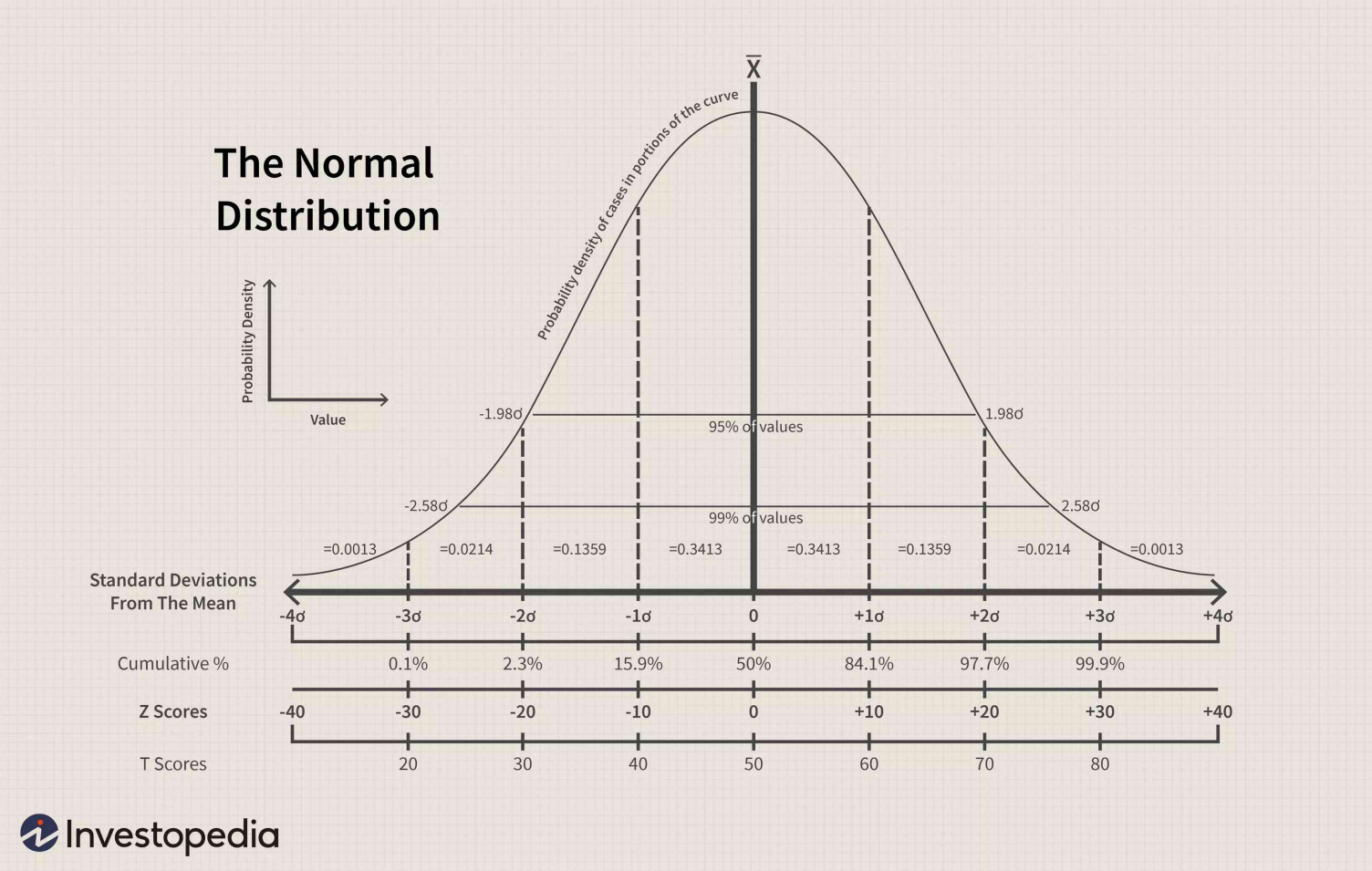
PC_4	PC_5	PC_6	PC_7
1.069917	0.798403	-0.178374	1.420791
0.711006	0.148932	-2.098136	0.142190
-1.686211	-0.811835	0.550774	0.539499
2.042134	1.036780	0.069152	-0.473741
-2.433367	0.480882	0.492603	1.306552

Hidden Markov Models

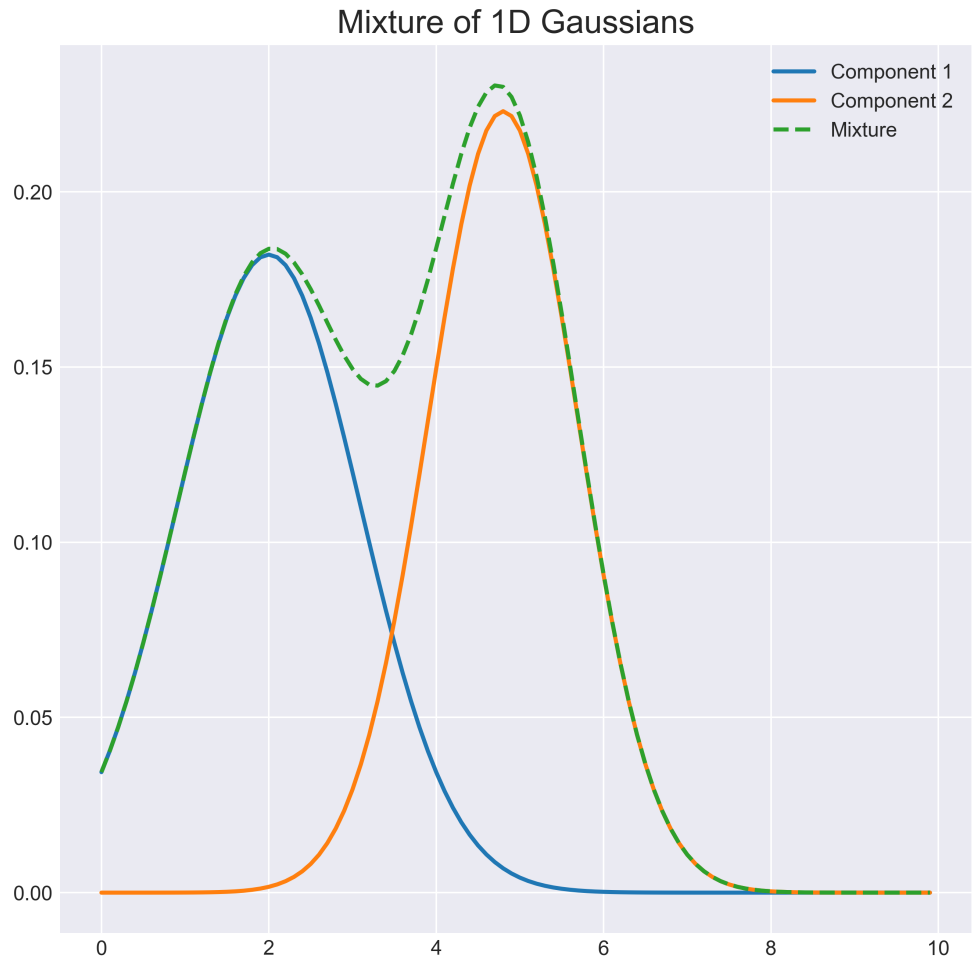
GUASSIAN DISTRIBUTION

Guassian Distribution = Normal Distribution = Bell-Shaped Curve

=



GUASSIAN MIXTURE MODELS



https://angusturner.github.io/generative_models/2017/11/03/pytorch-gaussian-mixture-model.html

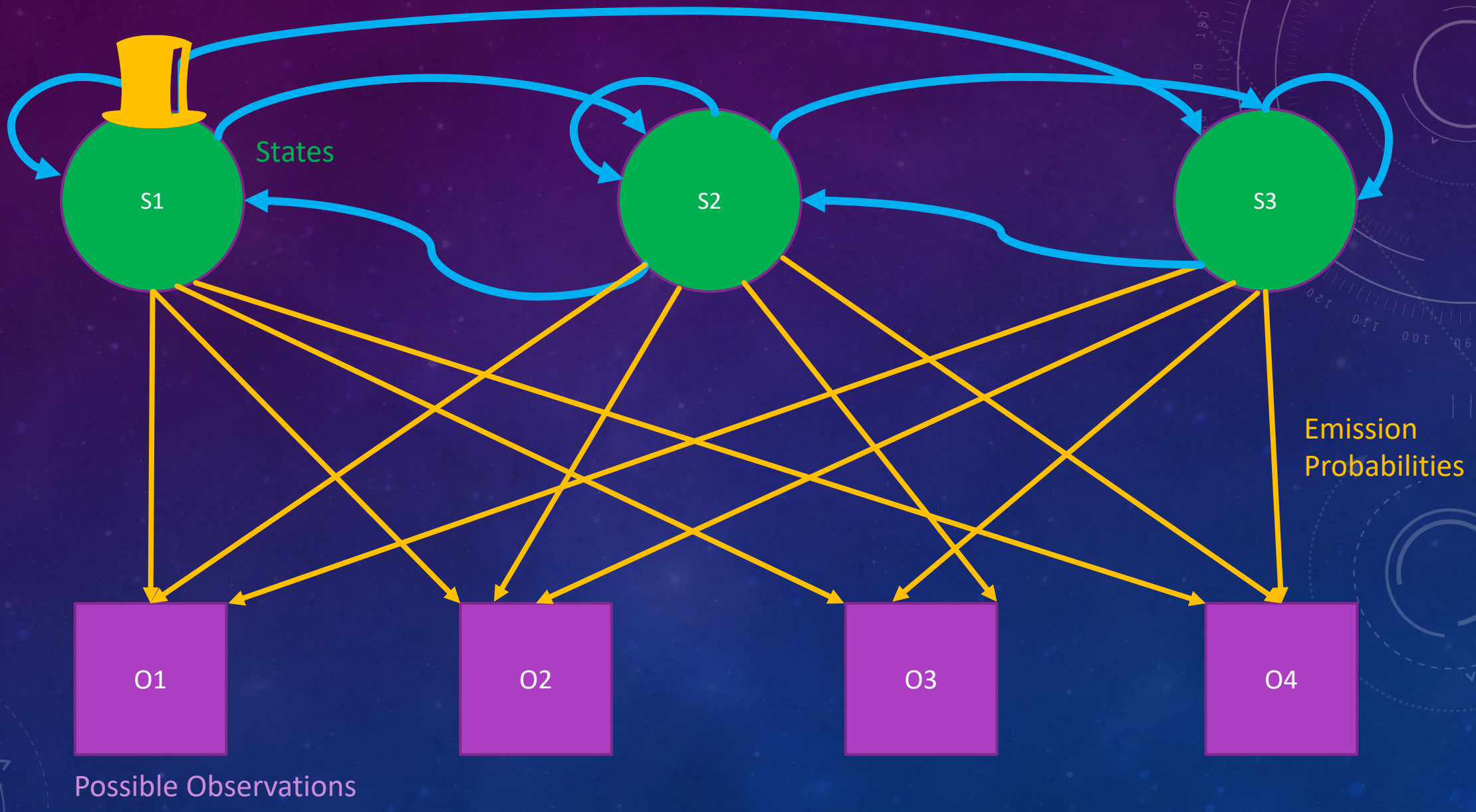
Example: A male bottleneck dolphin's length can vary between 96 and 150 inches long. Female's can vary between 89 and 144 inches long.

Imagine a dataset of dolphin's lengths. Would there be a way to label the probability that a dolphin is in one of two subgroups based on the dataset (population), without even knowing these are dolphins?

Yes – with Guassian Mixture Models, you can specify the number of subgroups you want to extract.

The unsupervised learning take care of the rest with some clever math.

HIDDEN MARKOV MODEL



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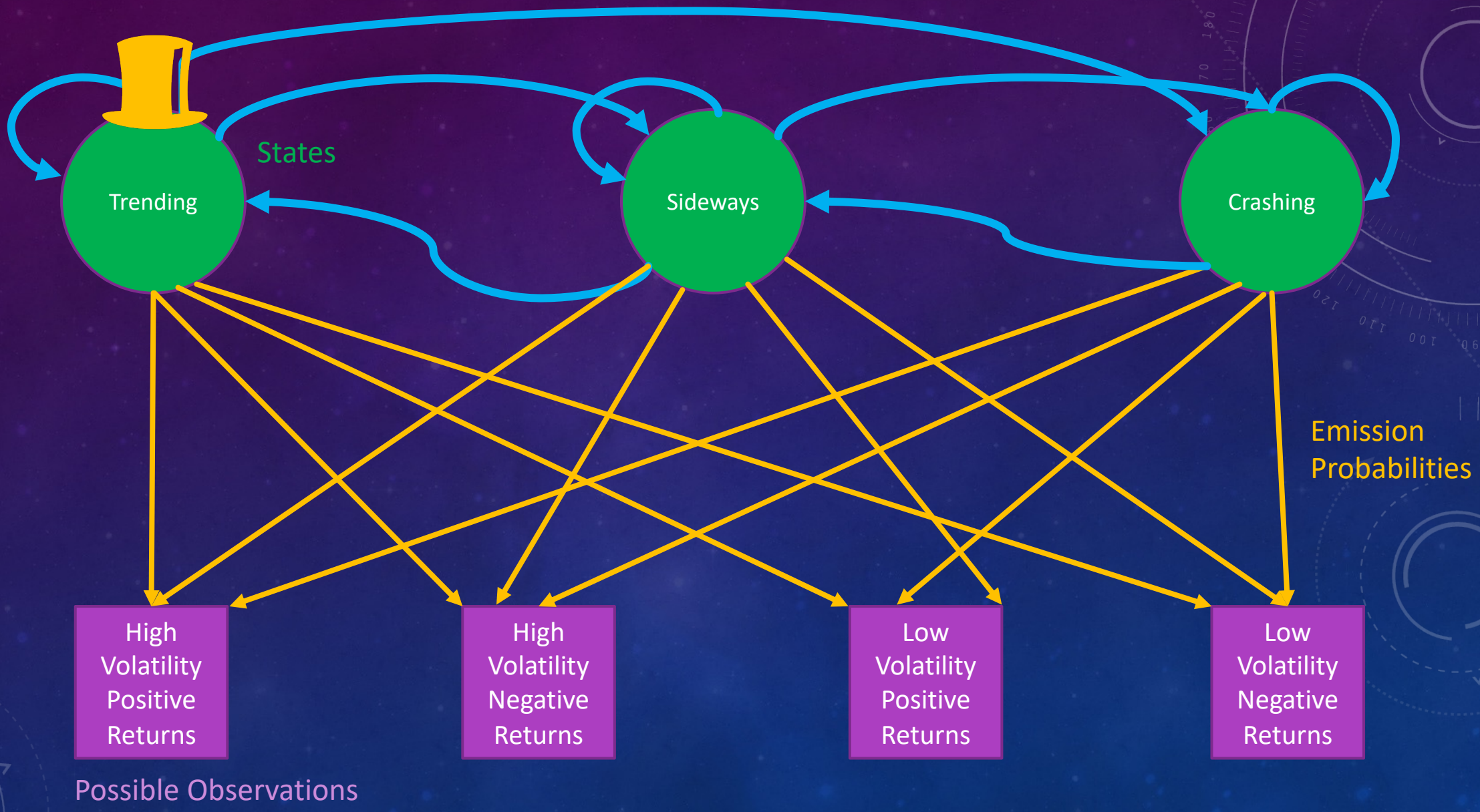
HIDDEN MARKOV MODEL



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HIDDEN MARKOV MODEL CONTINUED

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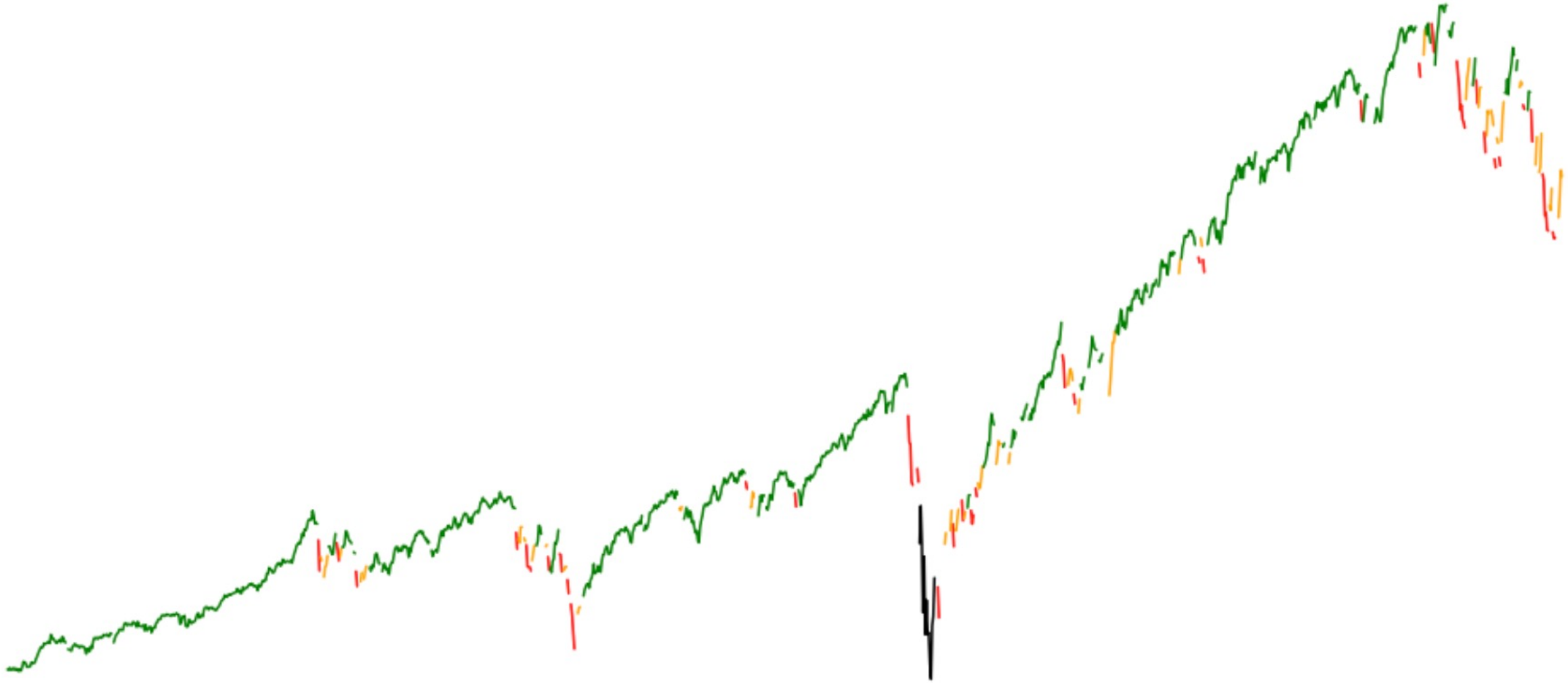
Observation (Returns)	+0.1	-0.02	-0.007	+0.04	+0.04	...
Observation (Volatility)	0.7	0.003	0.002	+0.7	0.5	...

Using Guassian Emissions

1) Find the optimal sequence of hidden states
2) Find the model likelihood
Viterbi algorithm and Forward-Backward Algorithm
3) Estimate the model parameters
Expectation-Maximization (EM) algorithm/Baum-Welch algorithm
https://hmmlearn.readthedocs.io/en/latest/tutorial.html

Probability Hidden State 1	0.95	0.80	0.30	0.15	0.97	...
Probability Hidden State 2	0.05	0.20	0.70	0.85	0.03	...

HIDDEN MARKOV RESULT - SPY



K-Means Clustering

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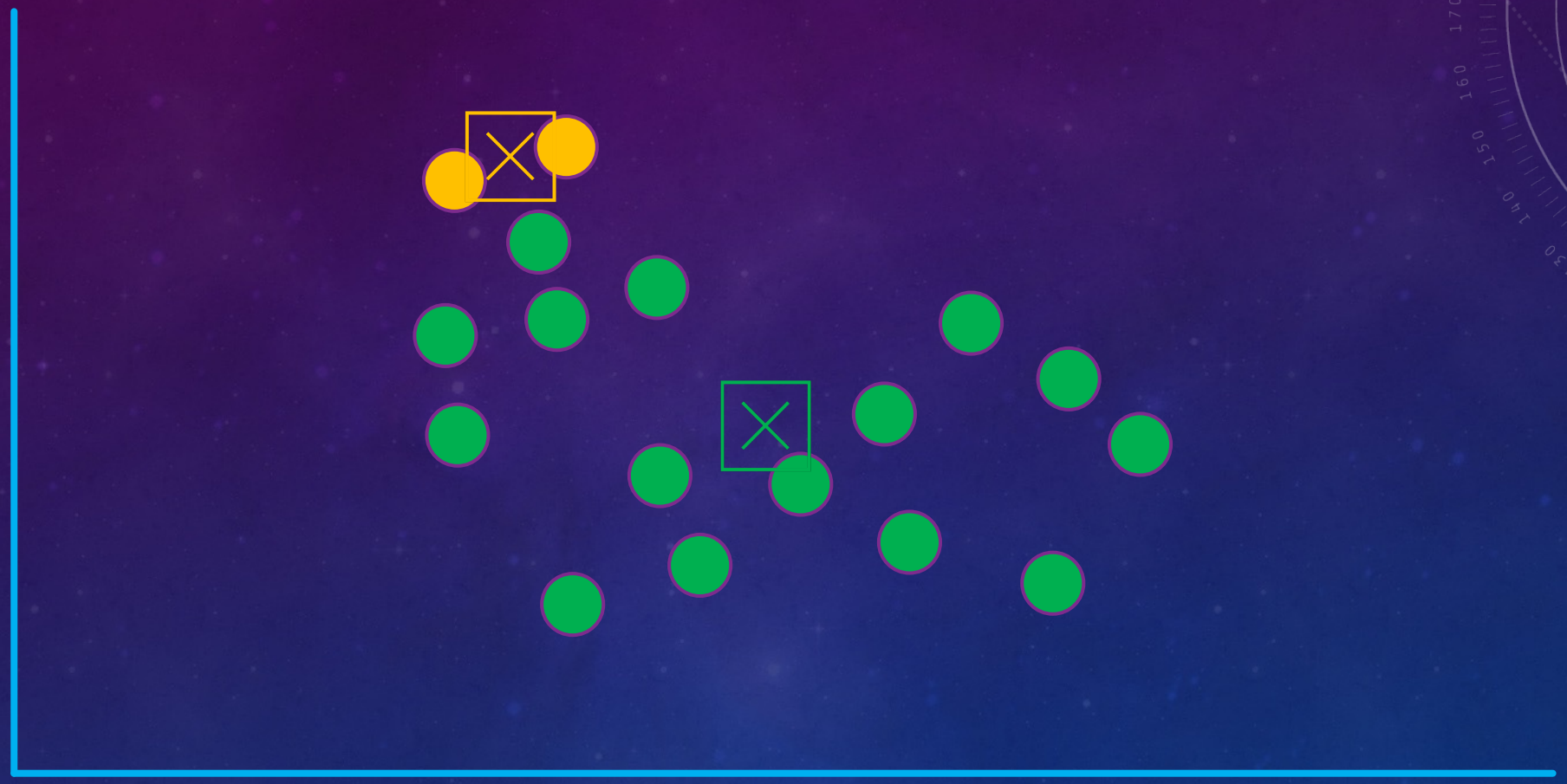
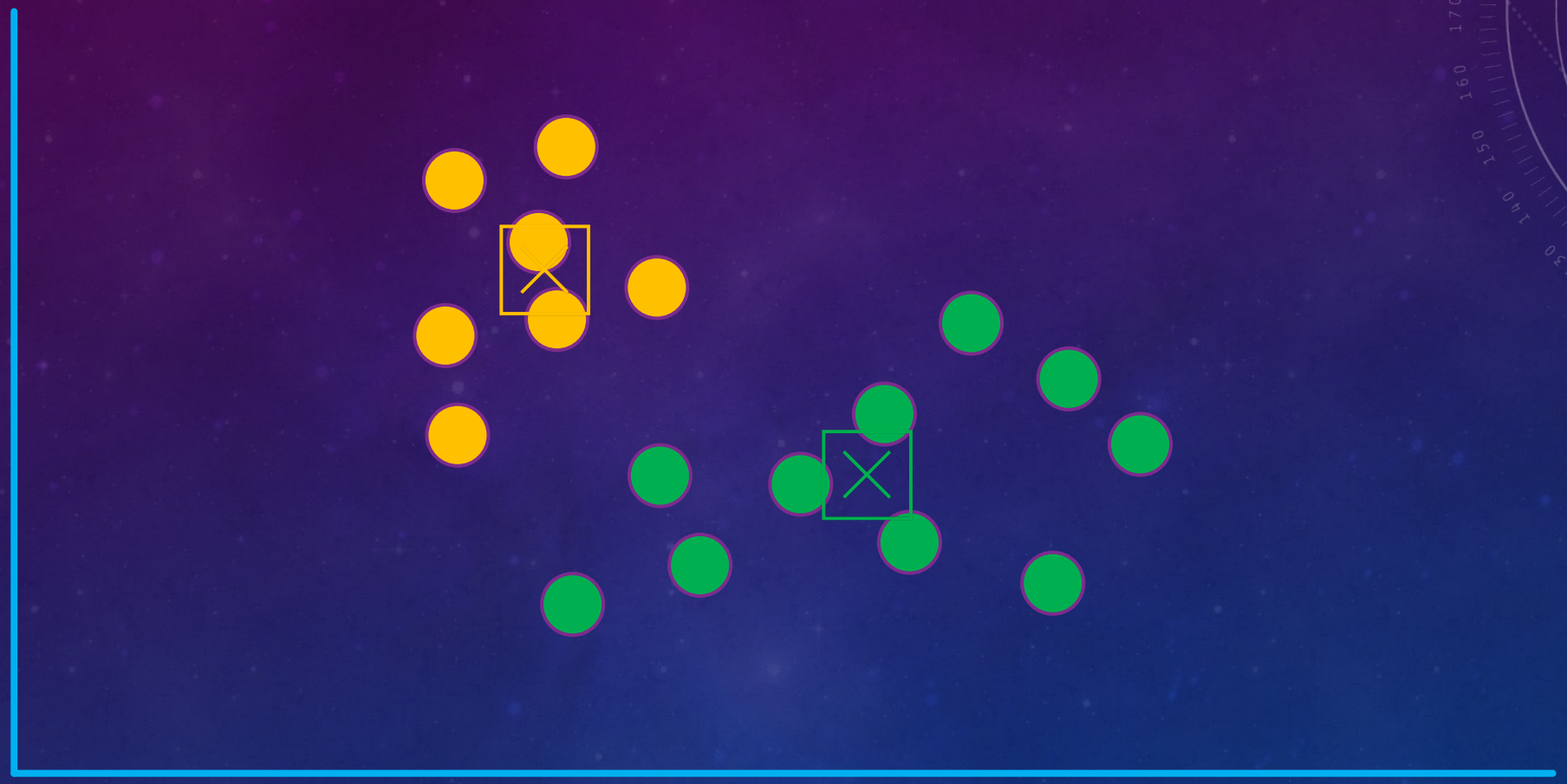




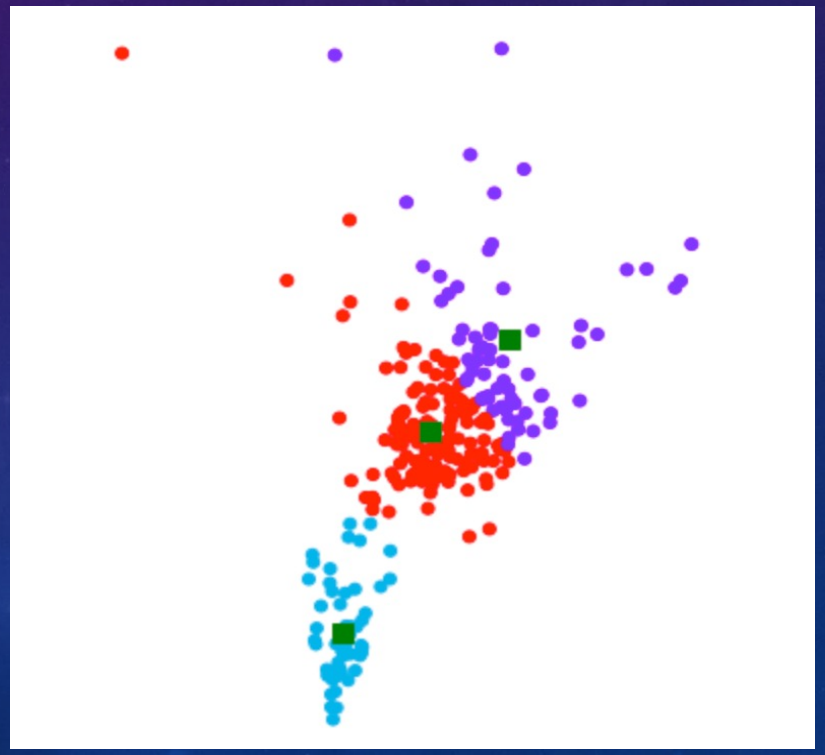
First Try

Second Try

And so on…

First Try

Second Try



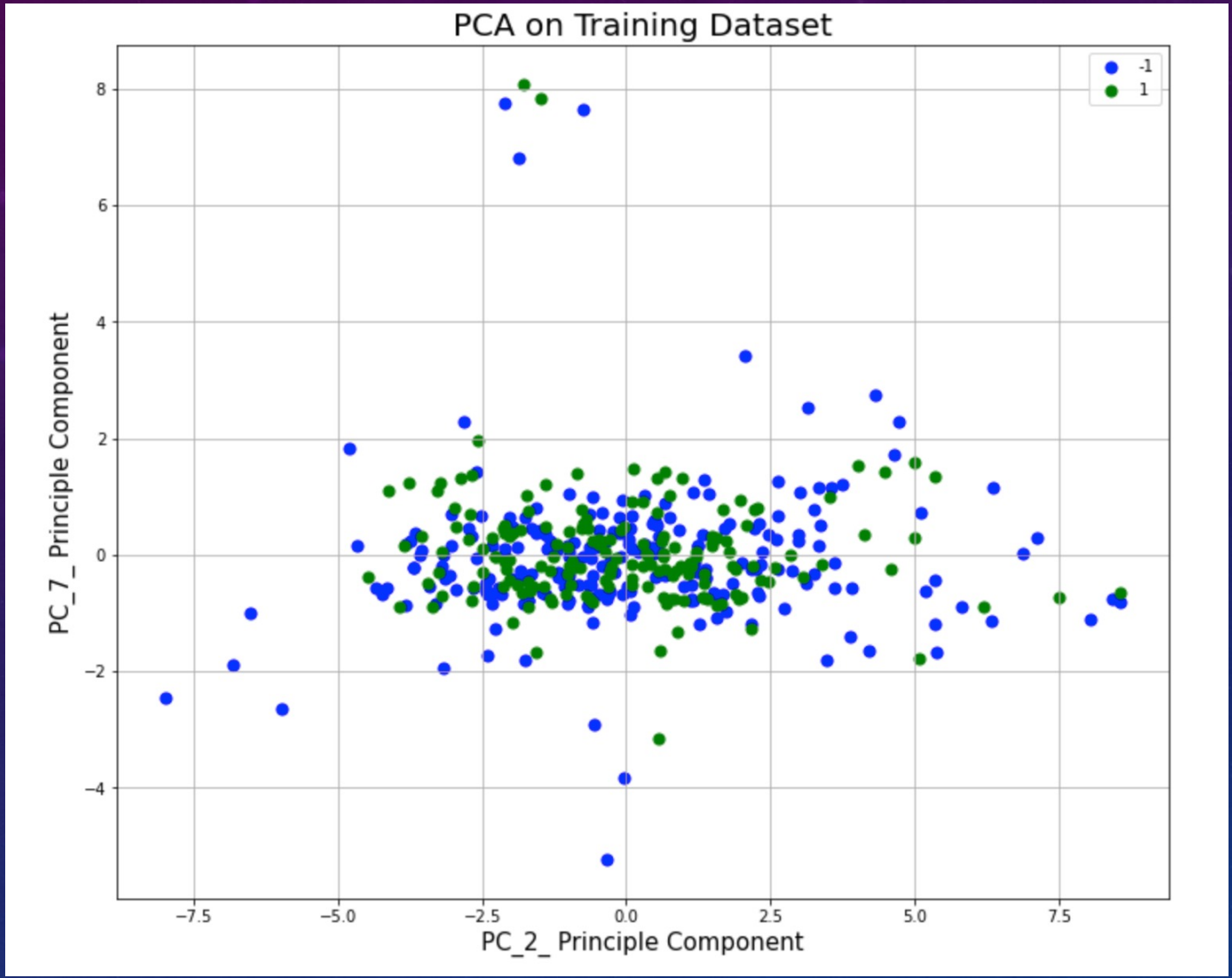
Principle Component Analysis

	High	Low	Open	Close	Adj Close	volume_mfi	volume_nvi	volatility_bbm	volatility_bbh	volatility_bbl	...	momentum_wr	momentum_ao	momentum_
Date														

	PC_0	PC_1	PC_2	PC_3	PC_4	PC_5	PC_6	PC_7
0	-4.663399	-0.247211	-2.611970	0.757772	1.069917	0.798403	-0.178374	1.420791
1	-1.816759	4.547170	-1.009873	0.755642	0.711006	0.148932	-2.098136	0.142190
2	2.026221	-4.735525	-0.753187	0.901963	-1.686211	-0.811835	0.550774	0.539499
3	-4.800988	0.887544	2.454545	-0.724577	2.042134	1.036780	0.069152	-0.473741
4	3.330988	-6.703617	0.524157	0.518986	-2.433367	0.480882	0.492603	1.306552

```
Variance of each component:  [0.40324648 0.18347369 0.08315292 0.04858102 0.03237307 0.02520932
 0.02367621 0.01896752]

 Total Variance Explained:  81.87
```


PCA on Training Dataset
-1
1
PC_7_ Principle Component
PC_2_ Principle Component
8
6
4
2
0
−2
−4
−7.5
−5.0
−2.5
0.0
2.5
5.0
7.5

SUPERVISED LEARNING

PHASE 3

Random Forests

Volume	Open	Close	TARGET
500	1.23	3.33	1
200	2.21	10.20	0
300	1.21	9.86	0
100	2.22	5.55	0
200	3.32	3.39	1
200	4.41	4.59	1
100	5.89	5.90	0

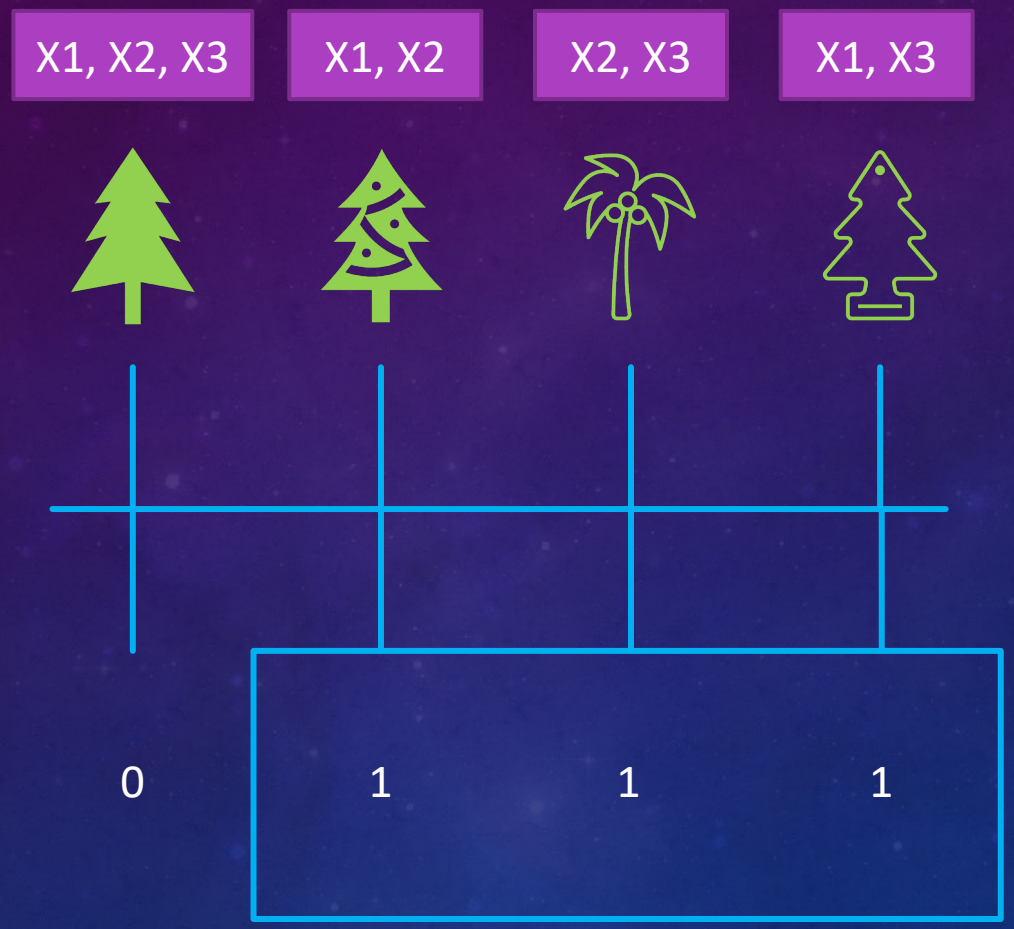
X1	X2	X3	y
500	1.23	3.33	1
200	2.21	10.20	0
300	1.21	9.86	0
100	2.22	5.55	0
200	3.32	3.39	1
200	4.41	4.59	1
100	5.89	5.90	0

X
X
Y
X

Vol
<500
1, 1, 1, 0, 0, 1
0, 0, 0, 0, 0, 0

Vol
<500
Close
<2.34
RSI
<0.1
etc...
Open
>0.2

Bagging



XGBOOST

Boosting

Deep Learning

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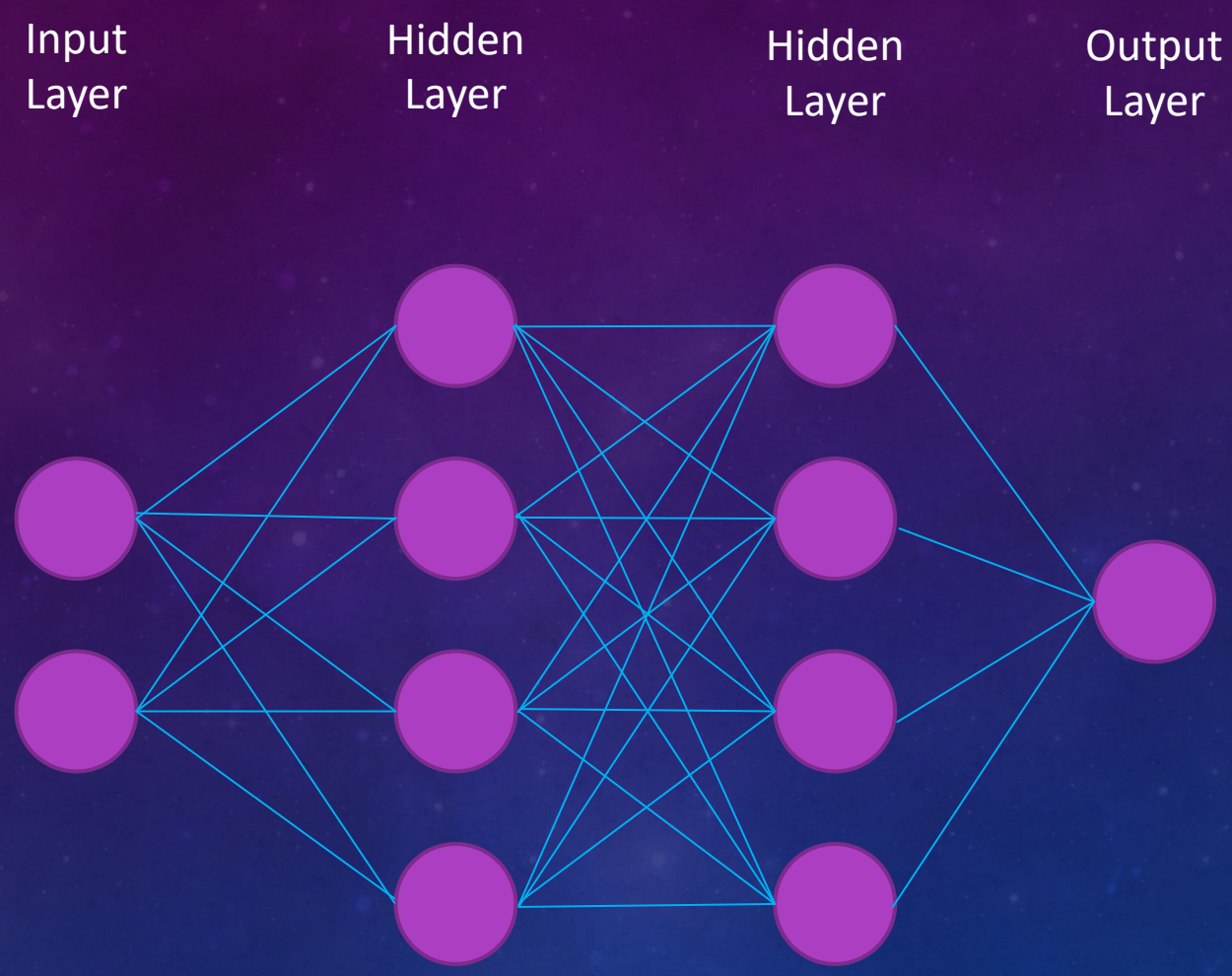

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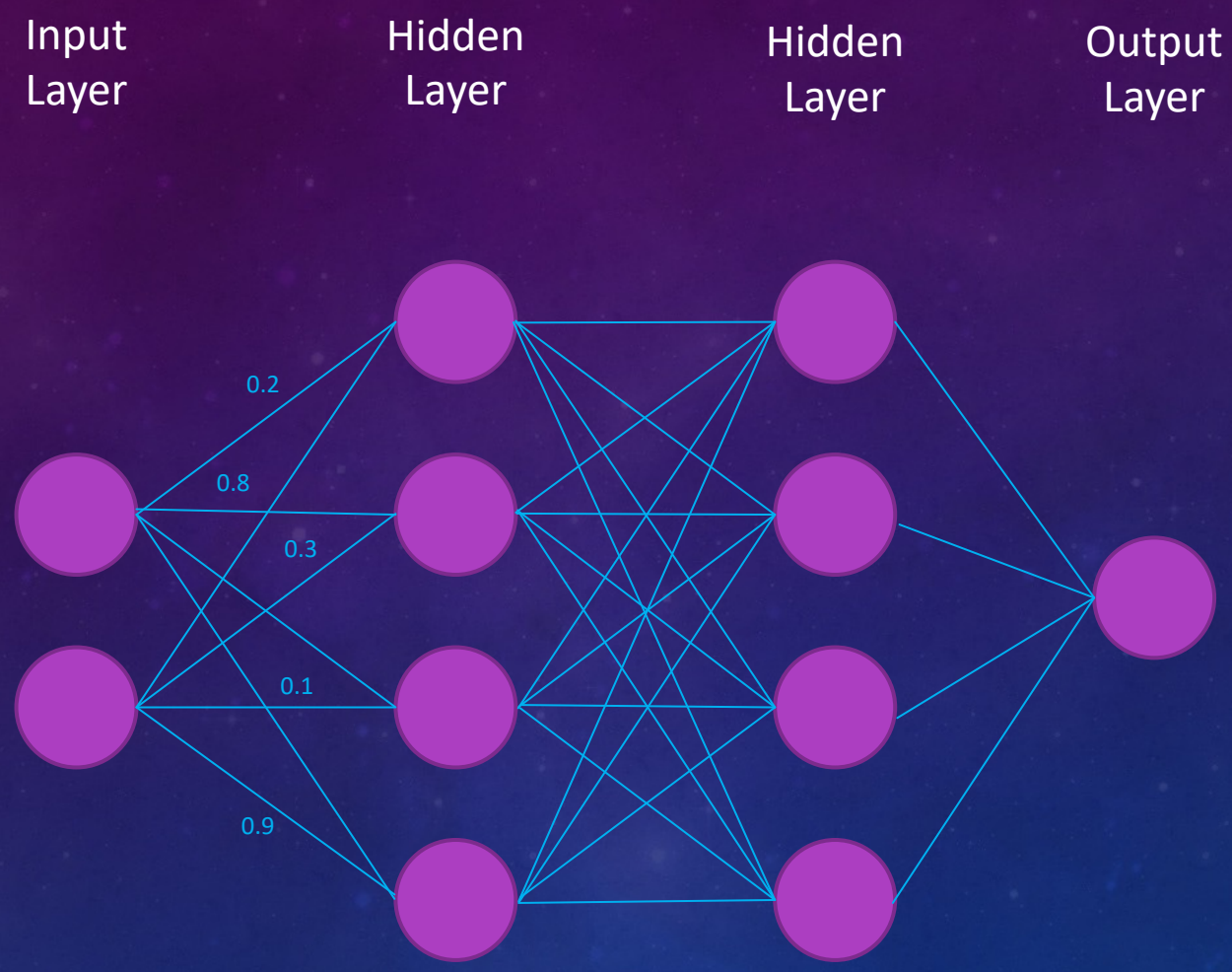
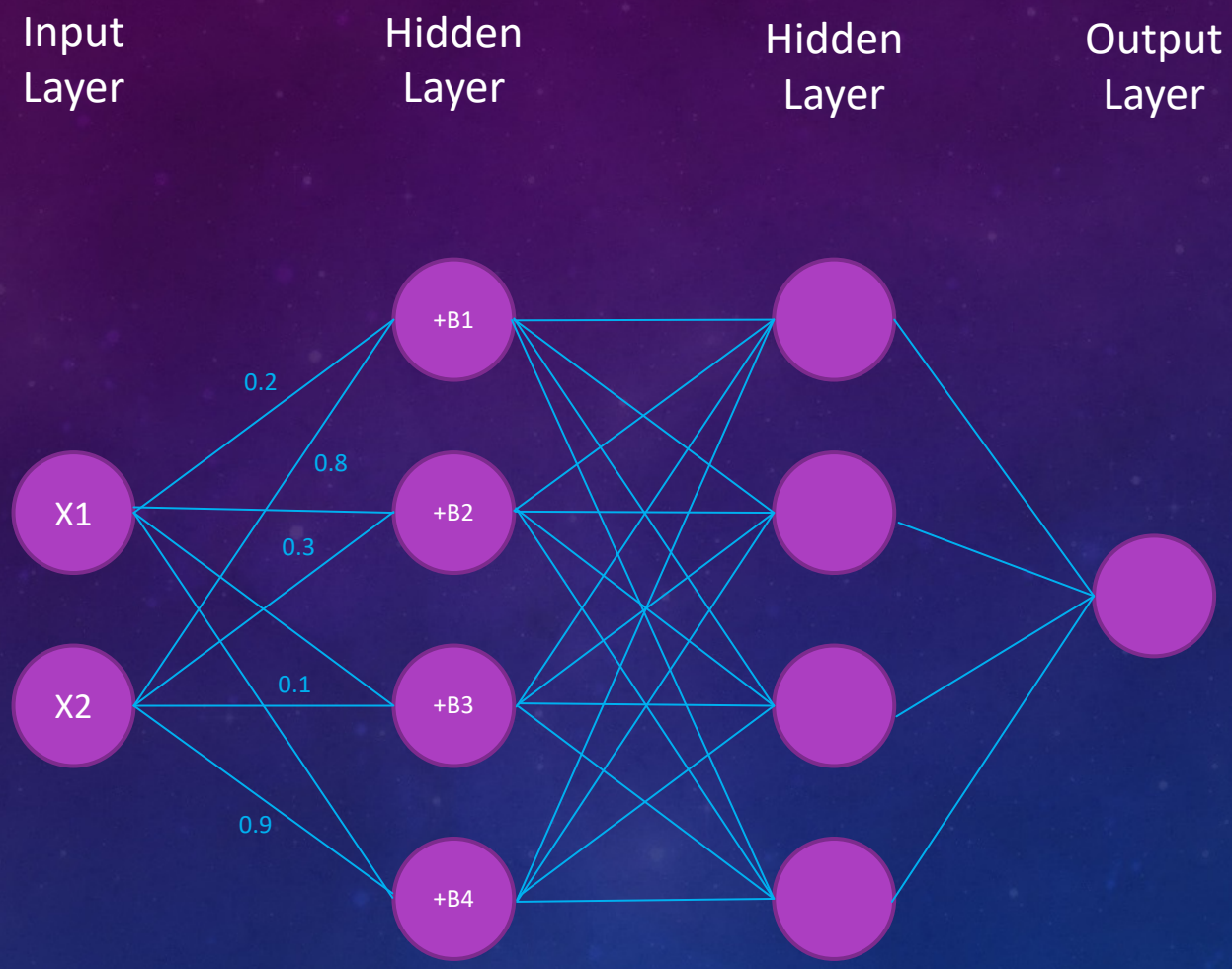
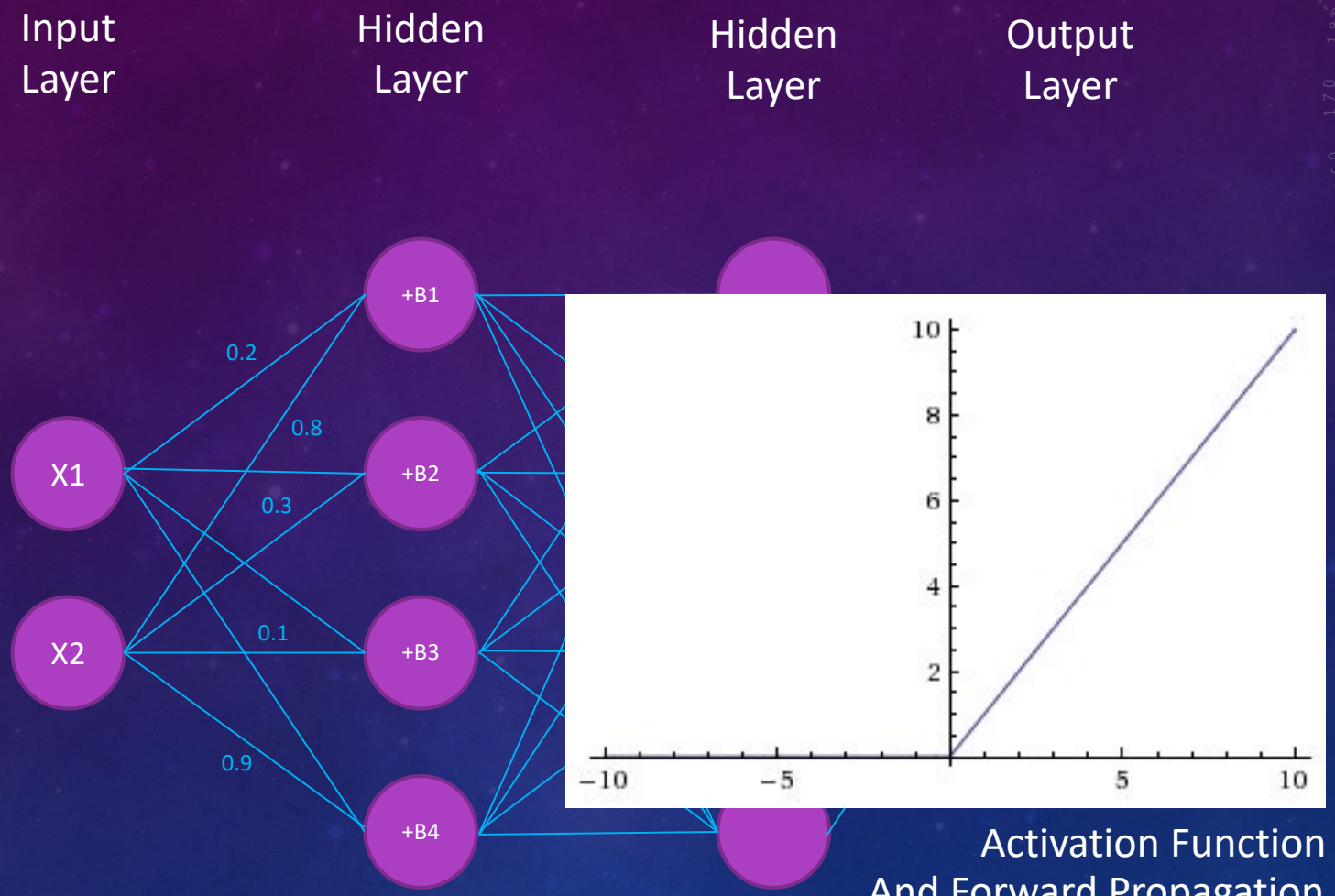
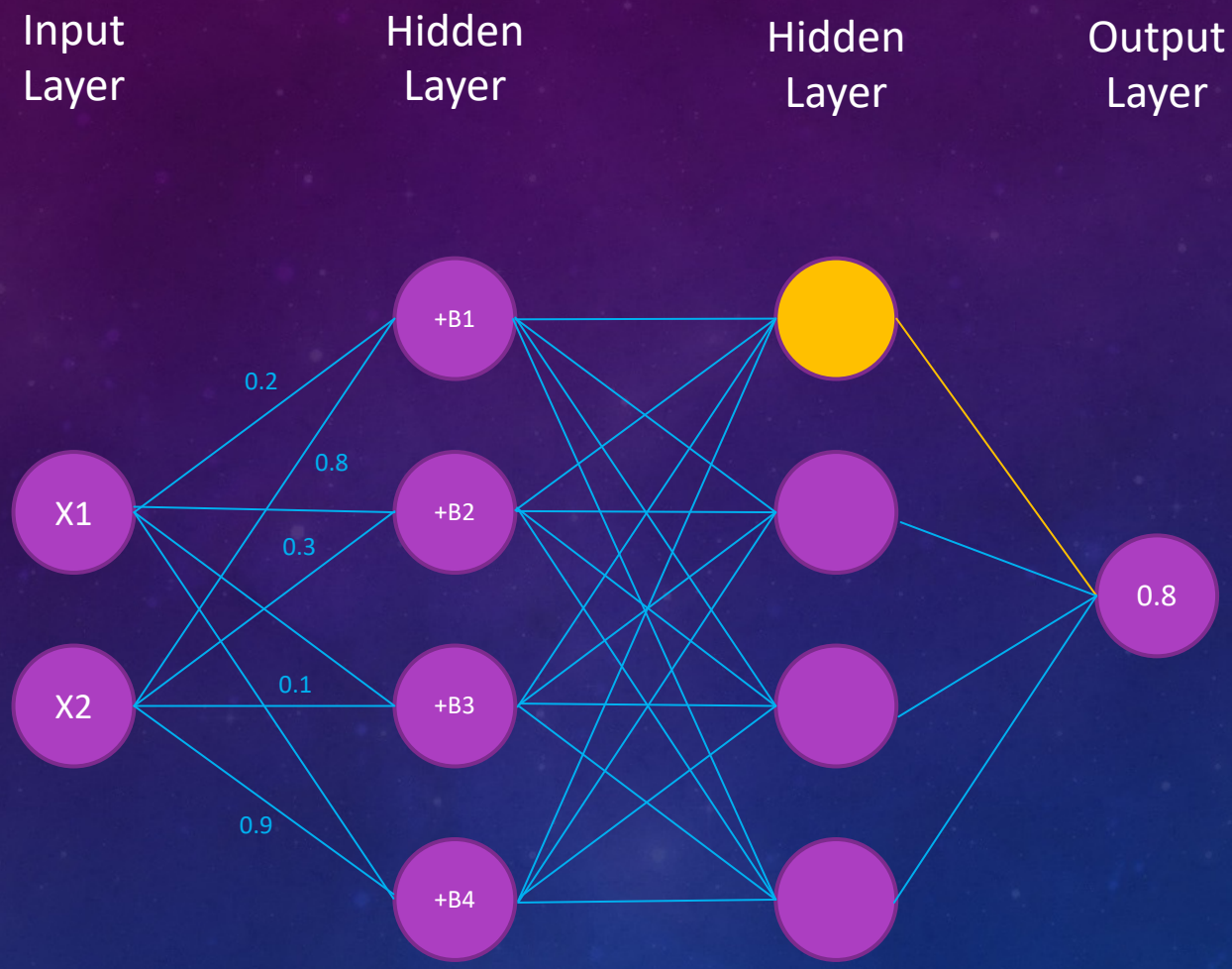


Crypto Wizards
Hunting for Edge

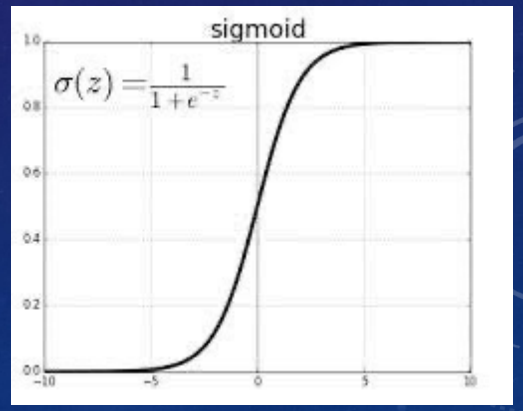




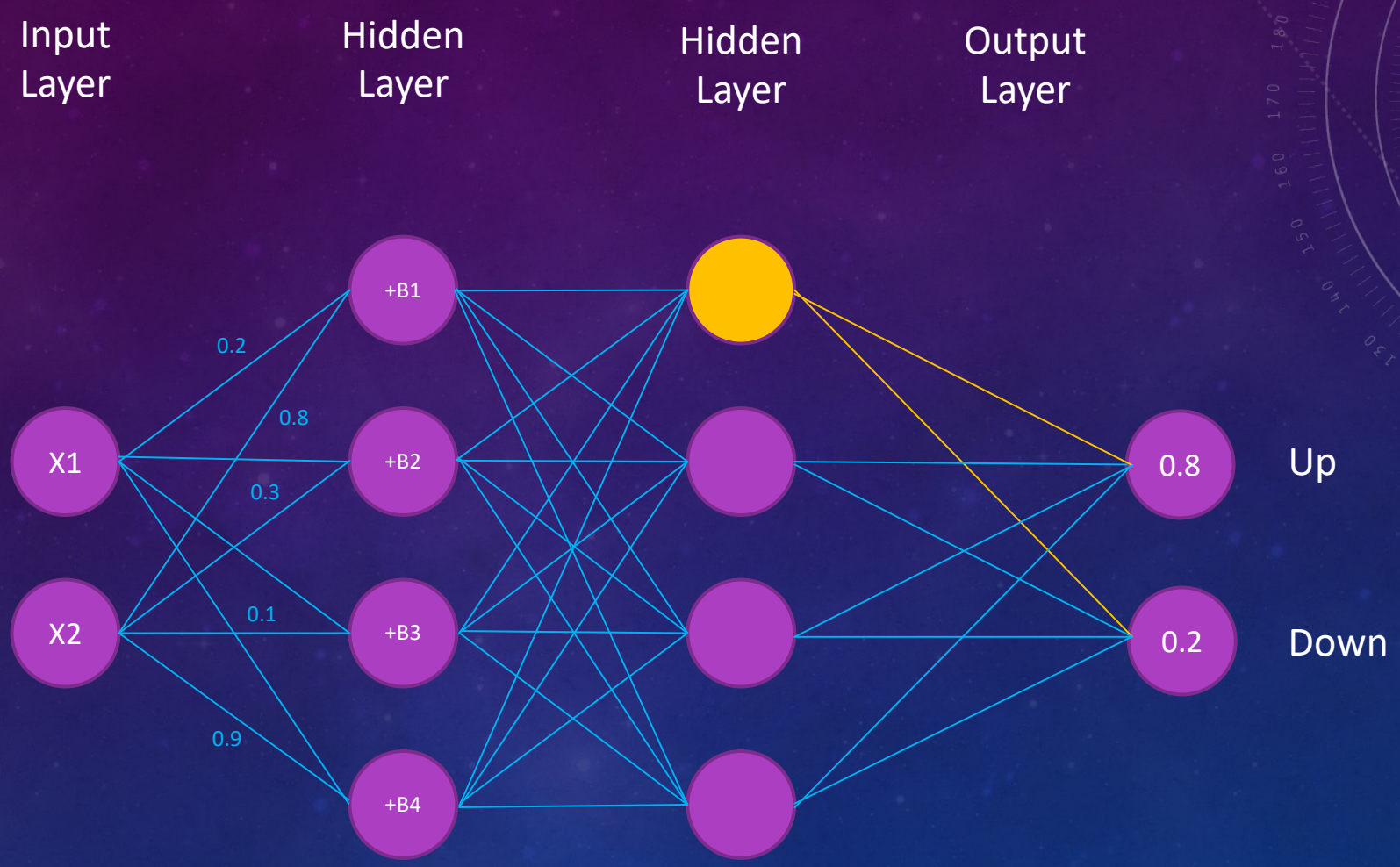
Activation Function
And Forward Propagation


Input Layer
Hidden Layer
Hidden Layer
Output Layer
X1
X2
+B1
+B2
+B3
+B4
0.2
0.8
0.3
0.1
0.9
0.8

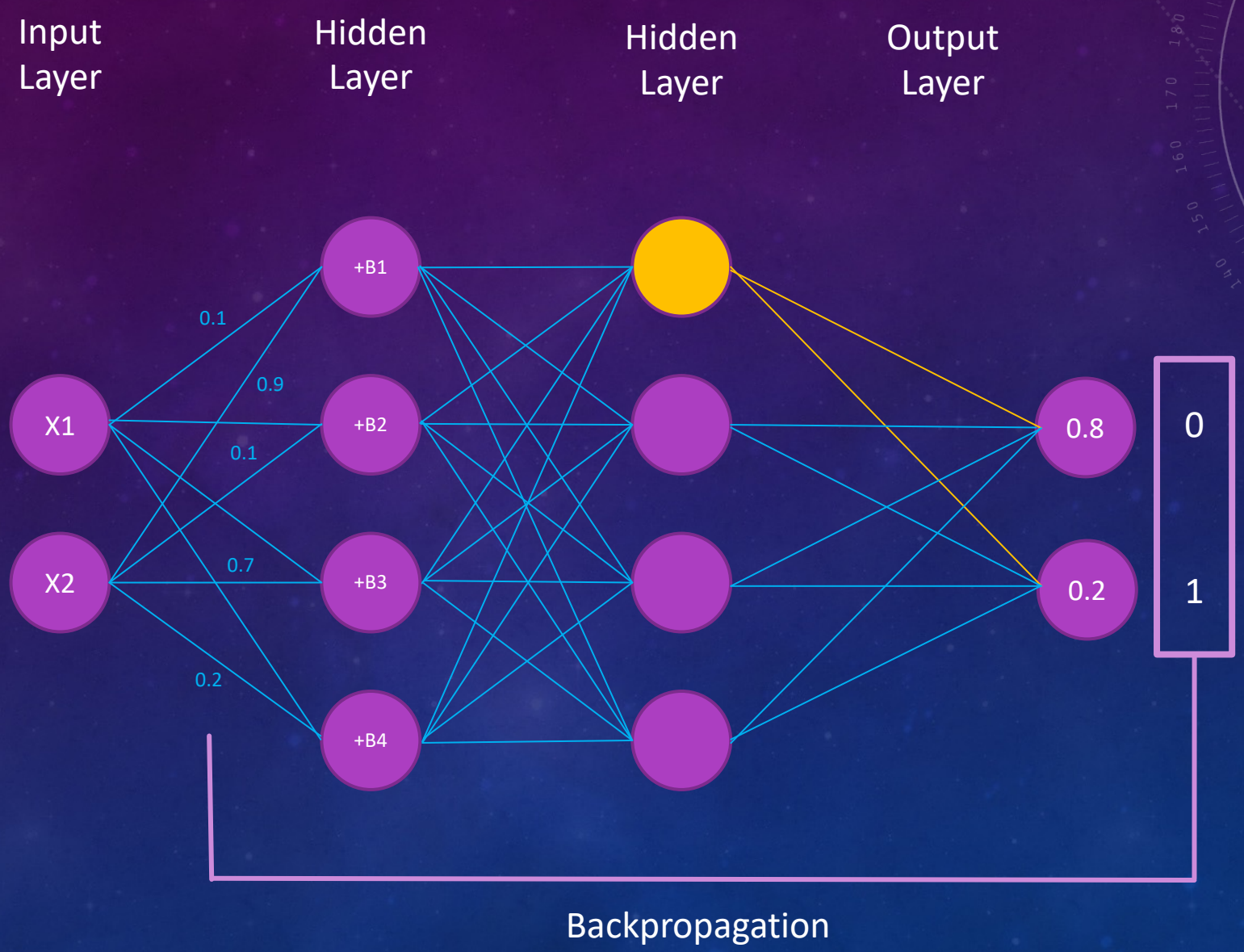
Prediction


sigmoid
$\sigma(z) = \frac{1}{1+e^{-z}}$

Crypto Wizards
Hunting for Edge



Crypto Wizards
Hunting for Edge



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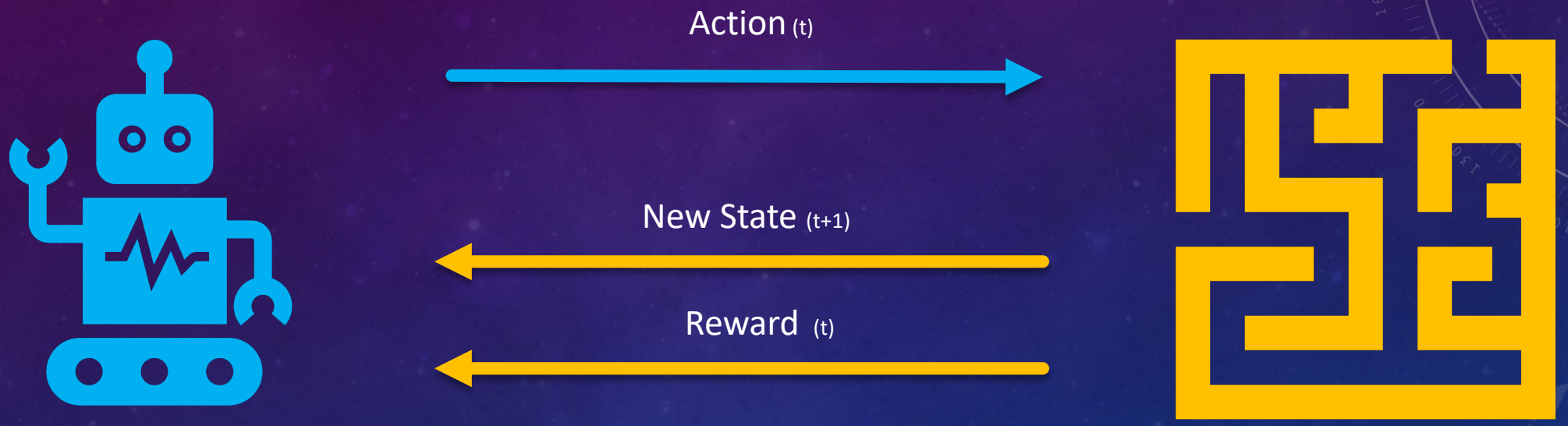
REINFORCEMENT LEARNING

PHASE 4

BUILD AN AGENT



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MAXIMIZE SUM OF THE DISCOUNTED REWARDS

TRAJECTORY

You are in State 0 (S0)

So you take Action 0 (A0)

This will put you in State (S1) and give you a Reward (R1)

So you take Action 1 (A1)

...

EPISODE

... You Reach Final State

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REWARD

R_1

RETURN

$R_1 + R_2 + R_3 + R_4 \ldots$

DISCOUNT FACTOR (y Gamma)

DISCOUNT REWARDS FURTHER FROM GOAL

ENCOURAGES YOU TO FIND THE OPTIMAL ROUTE

THIS WILL DICTATE HOW FAR INTO THE FUTURE THE AGENT CAN LOOK

$R_1 + {}_yR_2 + {}_y{}^2R_3 + {}_y{}^3R_4 \ldots$

GAMMA = 0, would mean that the agent would ignore all future states after the next move.

GAMMA = 0.99, the agent would look heavily to the future steps.

BELLMAN EQUATION for v(s)

$$V(s) = \max_{a} \left(R(s,a) + \gamma \sum_{s'} P(s,a,s')V(s') \right)$$

BELLMAN EQUATION for q(s, a)

$$Q^*(s,a) = \sum_{s',r} p(s',r|s,a)\left[r + \gamma \max_{a'} Q^*(s',a')\right]$$

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FINDING THE OPTIMAL POLICY $\pi*$

Using **Monte Carlo**

How do we ensure the model still explores?

Exploring Starts	vs	Stochastic
Every time agent faces environment, it starts in a random state and takes a random action		Has a probability of choosing every action of greater than zero. To ensure every action at some point gets taken.

More Realistic + Easier

FINDING THE OPTIMAL POLICY $\pi*$
Using **Monte Carlo**

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Stochastic Policies

On-Policy

vs

Off-Policy

The Same Policy that is being optimized, does the exploration as well.

e-greedy

Two policies are used:

1) An exploration policy
2) The policy being optimized

EXPLORATORY METHODS

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Continuous
State Spaces

Map Into Discrete State Spaces

Use Other Algorithms

State Aggregation (Bandings) or Tile Coding

Use Already Known Algorithms

DYNAMIC PROGRAMMING (DISCRETE SPACES)

- Monte Carlo
- Temporal Difference
- N Step Bootstrapping

MAKE CONTINUOUS DISCRETE

- State Aggregation
- Tile Coding

NEURAL NETS (CONTINUOUS SPACES)

- Deep SARSA
- Deep Q Learning
- Reinforce
- A2C
- PPO

PROXIMAL POLICY OPTIMIZATION – A POLICY GRADIENT METHOD

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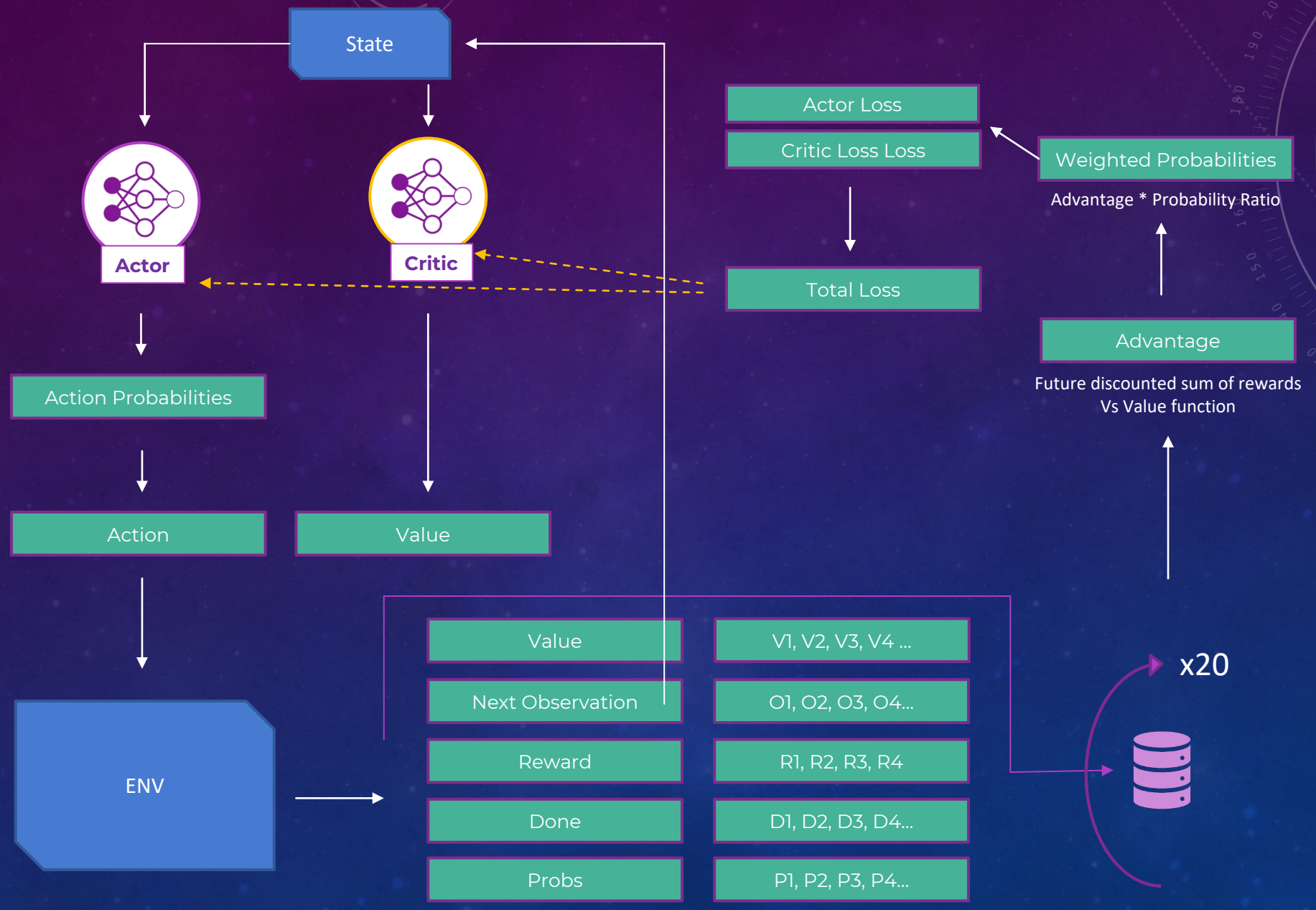

REINFORCE POLICY GRADIENT

Policy Gradient Method (Where the Neural Network IS the Policy)

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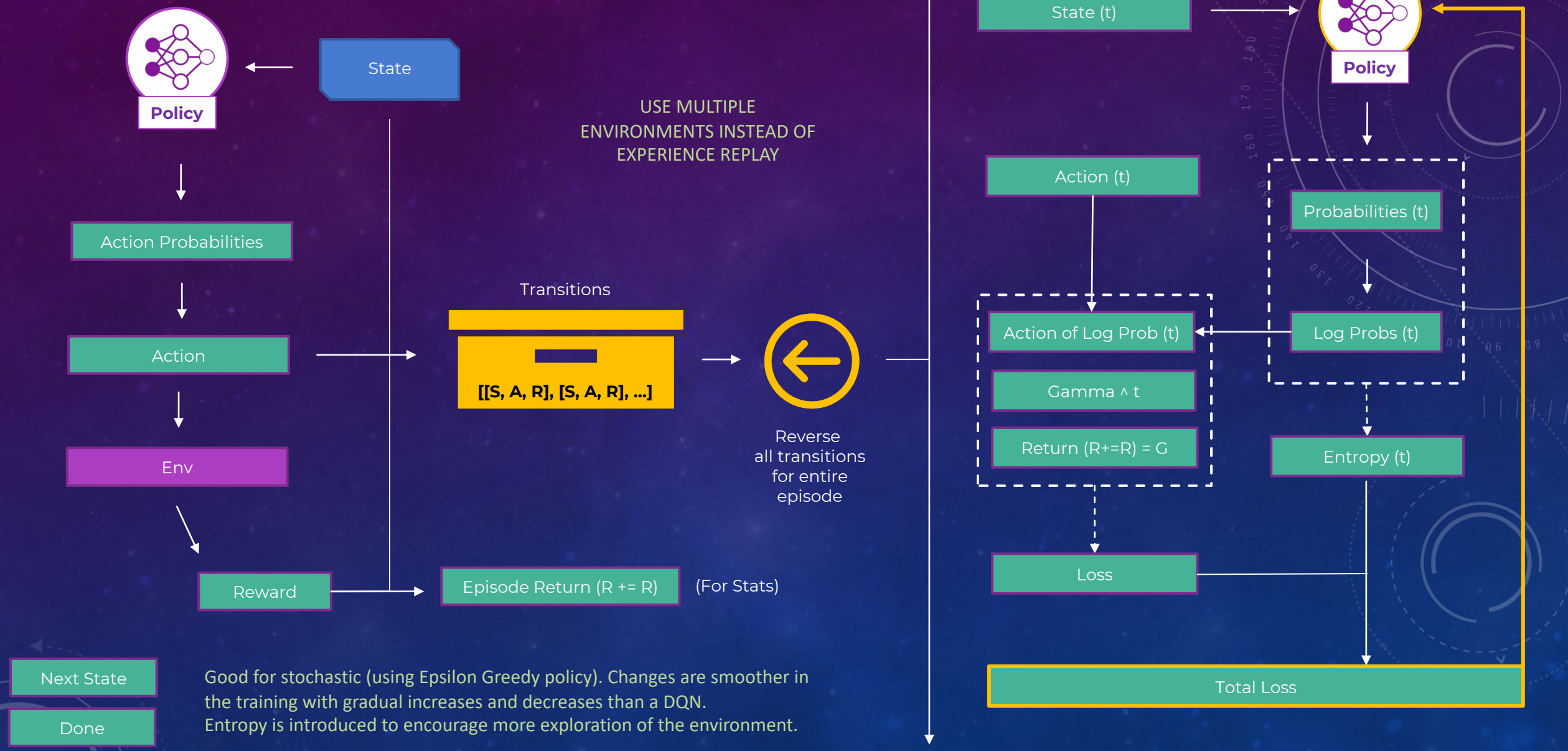

Good for stochastic (using Epsilon Greedy policy). Changes are smoother in the training with gradual increases and decreases than a DQN.
Entropy is introduced to encourage more exploration of the environment.