



# GPU Accelerated Backtesting and ML for Quant Trading Strategies

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- Goals
  - Execute automated algorithmic trading strategies
  - Optimize risk return
- Procedure
  - Extract signals and build price forecasting indicators from market data
  - Transform indicators into buy / sell decisions
  - Apply portfolio risk management
- Challenges
  - Find relevant signals and indicators
  - Engineer and parameterize trading decision
  - Find optimal parameters
- Approach
  - Exploit parallelism in the computations
  - Accelerate calculations by using a GPU cluster

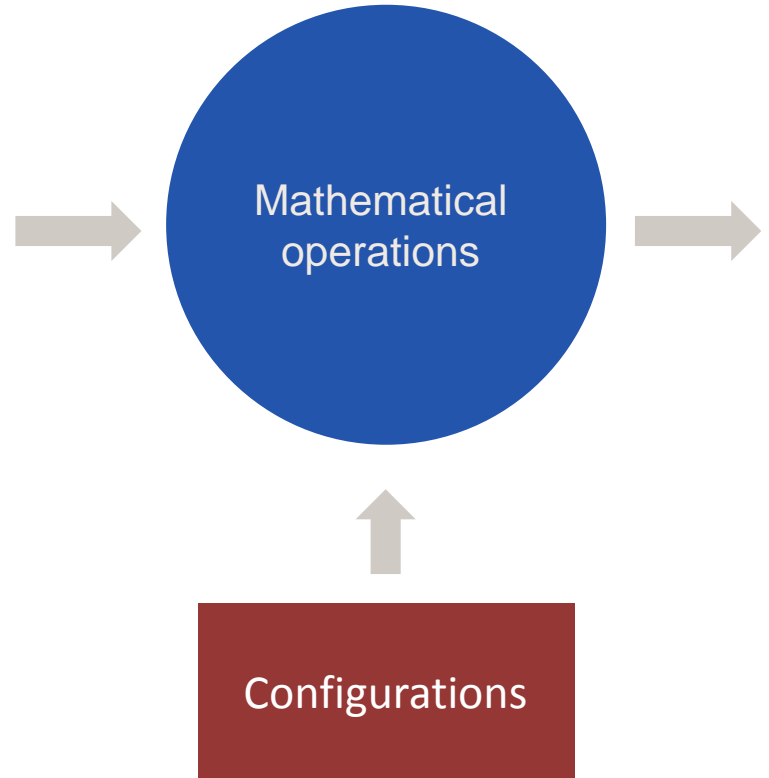
# Algo Trading Strategies

Market data

Rules

Trading decision

Symbol	Pct	Last	Change	Prev	Bid	Ask	High	Low	Etol	Volume
ES #F	+0.11%	136400	+150	136250	136400	136420	136825	134250	1084556	2078198
SP #F	+0.13%	136430	+180	136250			136820	134210	2111	10585
\$SPX	-0.08%	1368.39	-0.21	1368.10			1370.08	1363.94		
NQ #F	+0.20%	263200	+650	262550	263175	263200	264150	258550	160303	320105
\$NDX	+0.01%	2638.09	+0.17	2637.82			2644.37	2620.95		
\$COMPO	-0.04%	2958.09	-0.21	2958.34			2960.87	2939.21		
YM #F	+0.03%	1294600	+300	1295700	1294500	129460	1296200	1277900	78289	138189
DJ M2	-0.02%	1295500	-300	1295700	1295000		1296000	1291000	0	131
DJ #F	-0.02%	1295500	-300	1295700	1295000		1296000	1291000	0	131
ES U2	+0.17%	135825	+225	135600	135750	135800	135975	133750	908	1679
\$INDU	-0.27%	13003.04	-35.33	13038.27			13035.15	12970.00		43960296
TF #F	+0.20%	78940	+300	78640	78930	78840	79140	77200	86434	153710
\$RUT	-0.26%	791.34	-0.50	791.84			792.67	788.07		
MG #F	+0.20%	96330	+280	96050	96320	96340	96630	94660	15015	26228
NK #F	-1.13%	9155	-105	9260			9155	9155	0	3315
\$TRAN	+0.07%	5257.48	+29.84	5227.64			5257.62	5158.00		4747289
ZB #F	+0.00%	14324	+5	14322	14324	14326	14419	14221	142139	323844
US M2	+0.07%	14325	+3	14322			14325	14325	0	323844
\$TYX	-0.20%	3.065	-0.006	3.071			3.070	3.052		
ZN M2	+0.01%	132210	+5	132205	132210	132215	133020	132195	484043	1299349
TY M2	+0.34%	132205	+145	132060			132210	132210	0	1299349
\$TNX	-0.37%	1.873	-0.007	1.880			1.880	1.859		
ZF M2	+0.02%	123207	+7	123200	123207	123310	124032	122997	170942	405572
ZT M2	-0.01%	110087	-8	110090	110087	110090	110092	110082	59470	122419
6E M2	-0.08%	13052	-37	13089	13051	13052	13062	12957	190719	237586
6S M2	-0.20%	10888	-33	10901	10887	10888	10877	10778	35792	39657
6B M2	+0.20%	19183	+42	19141	19182	19184	19183	19110	84892	84455
6J M2	+0.01%	12528	+1	12525	12525	12525	12524	12504	48336	78990
6A M2	+0.20%	10160	+20	10140	10159	10160	10165	10065	83072	160296
6C M2	+0.10%	10048	+10	10038	10047	10048	10060	10002	60345	103796
6N M2	+0.00%	7934	+4	7930	7934	7936	7945	7886	11427	18113
6X M2	+0.10%	79705	+115	79587	79705	79710	80135	79660	17688	24757



Input

Configurations

Output



# Example



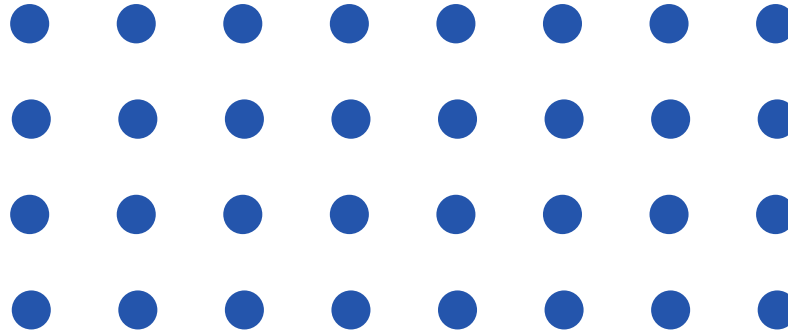
Buy signal

Sell signal

- Futures market
  - CME 50 liquid futures
  - Other exchanges
- Equity markets
  - World stock indices
- FX markets
  - 10 major currency pairs
  - 30 alternative currency pairs
- Options markets
  - Options on futures
  - Options on indices

# Strategy Universe

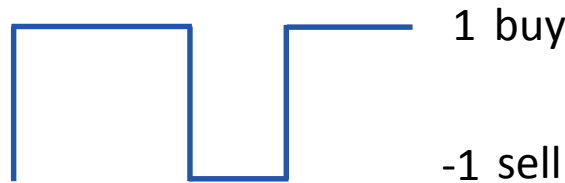
Strategy configurations



Configuration  $c$



Trading decision  $s(c)$

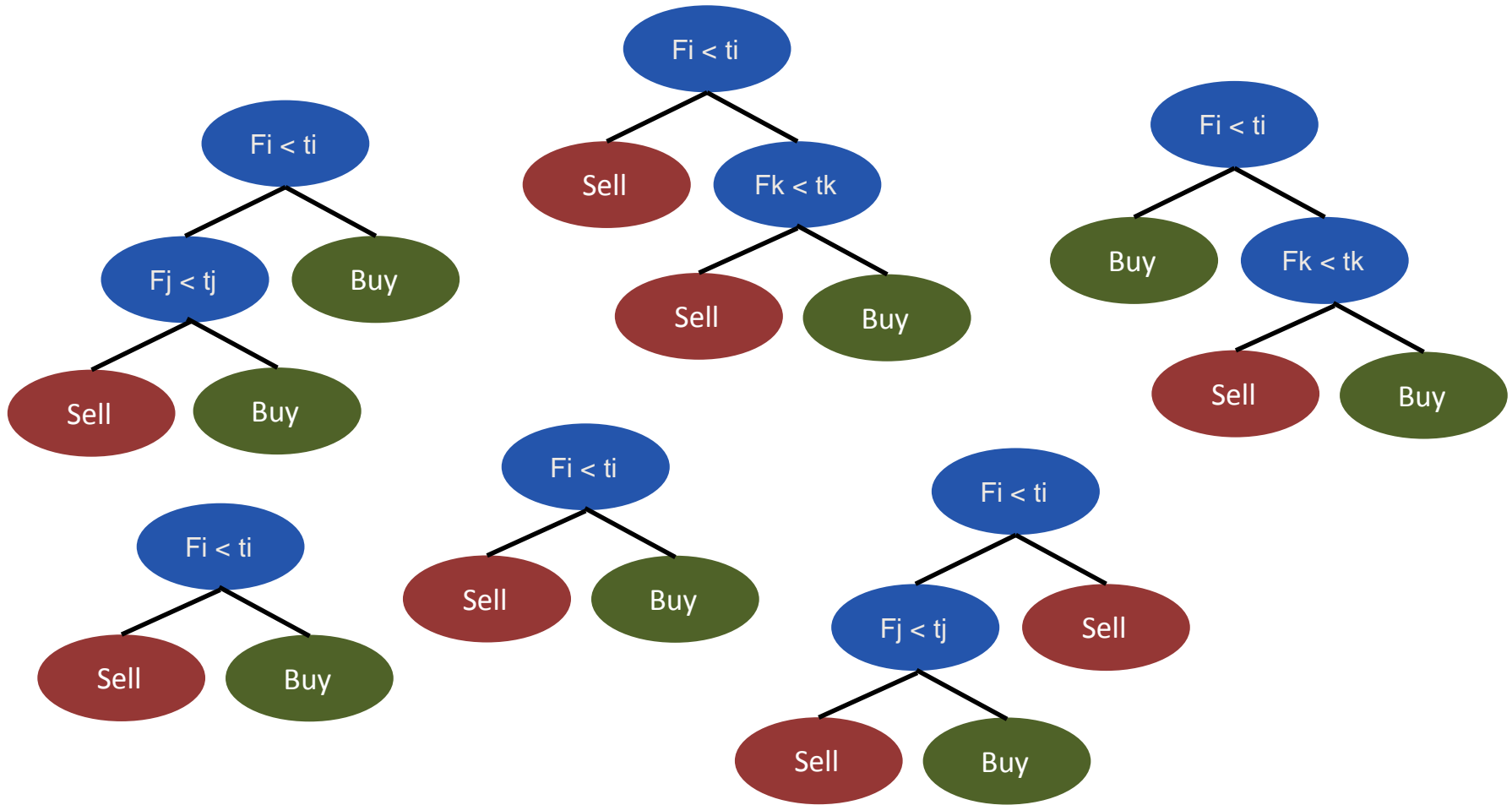


Utility  $U(s(c))$

P&L / drawdown

Challenge 1: How can we engineer a strategy producing buy / sell decisions ?

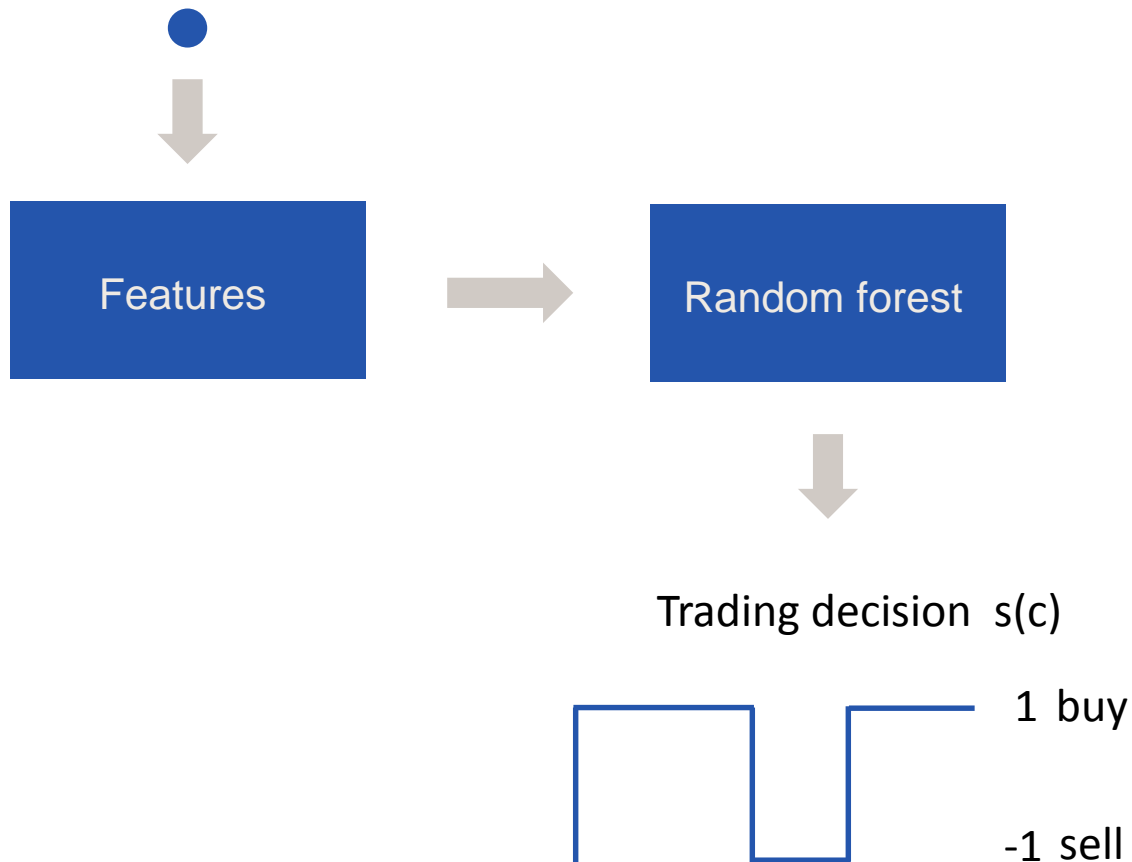
# Random Forests





# Random Forests

Strategy configuration  $c$



Bootstrapping to create training sets

C 4.5 algorithm for individual tree construction

- Selecting subset of features for tree construction
- Each node is associated with a subset of training samples
- Recursive, starting at the root node
- At each node execute divide and conquer algorithm to find locally optimal choice
  - If samples are in same class (or few class) node is a leaf associated with that class
  - If samples are in two or more classes
    - Calculate information gain for each feature
    - Select feature if largest information gain for splitting

# Entropy

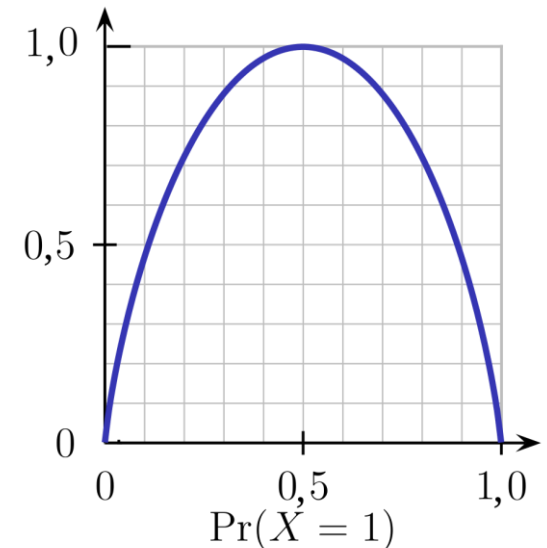
$T$  = set of samples associated with node

$C_1, \dots, C_n$  = classes of samples

Entropy

$$Ent(T) = - \sum_{i=1}^n \frac{freq(C_i, T)}{|T|} \log_2 \left( \frac{freq(C_i, T)}{|T|} \right)$$

- Characterizes impurity of samples
- Measure of uncertainty
- Additive: impurity of several subsets is sum of impurities



$T_1, \dots, T_s$  = subsets of  $T$  generated by splitting on selected attribute

Information gain discrete feature

$$gain(T_1, \dots, T_s) = Ent(T) - \sum_{i=1}^s \frac{|T_i|}{|T|} Ent(T_i)$$

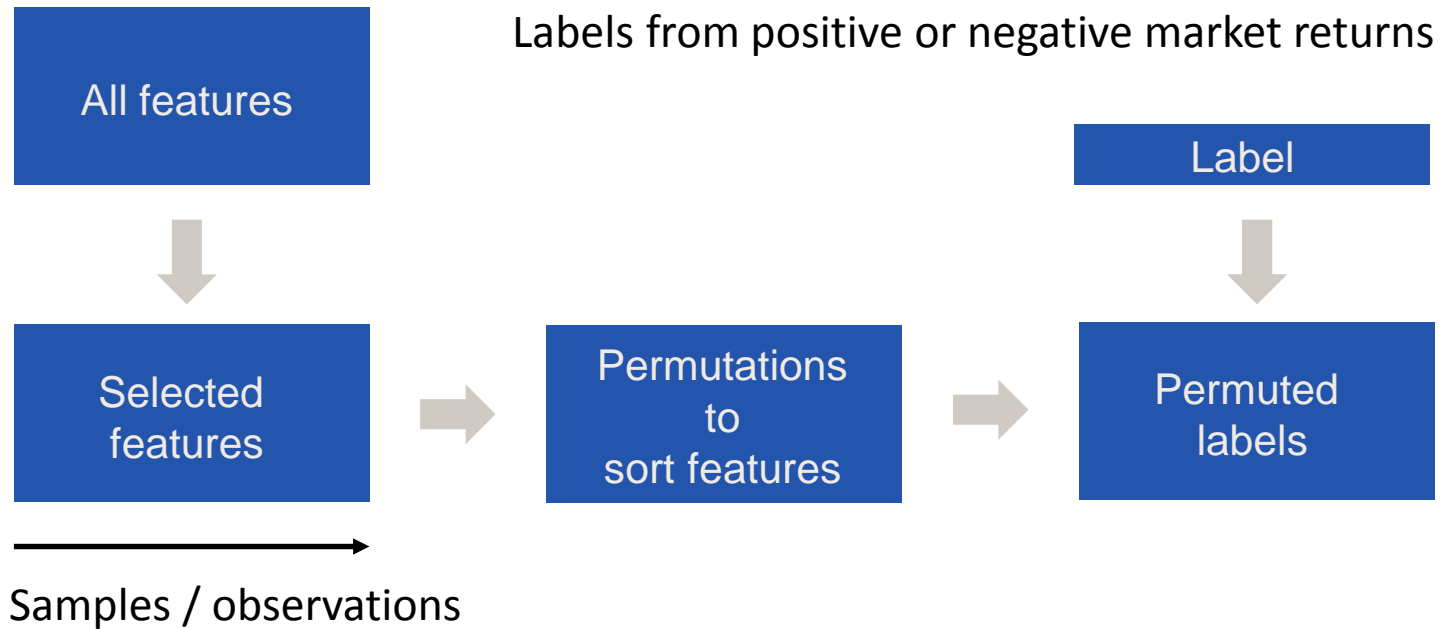
Information gain continuous feature with optimal splitting threshold

$$gain(t) = gain(T_{\leq t}, T_{> t})$$

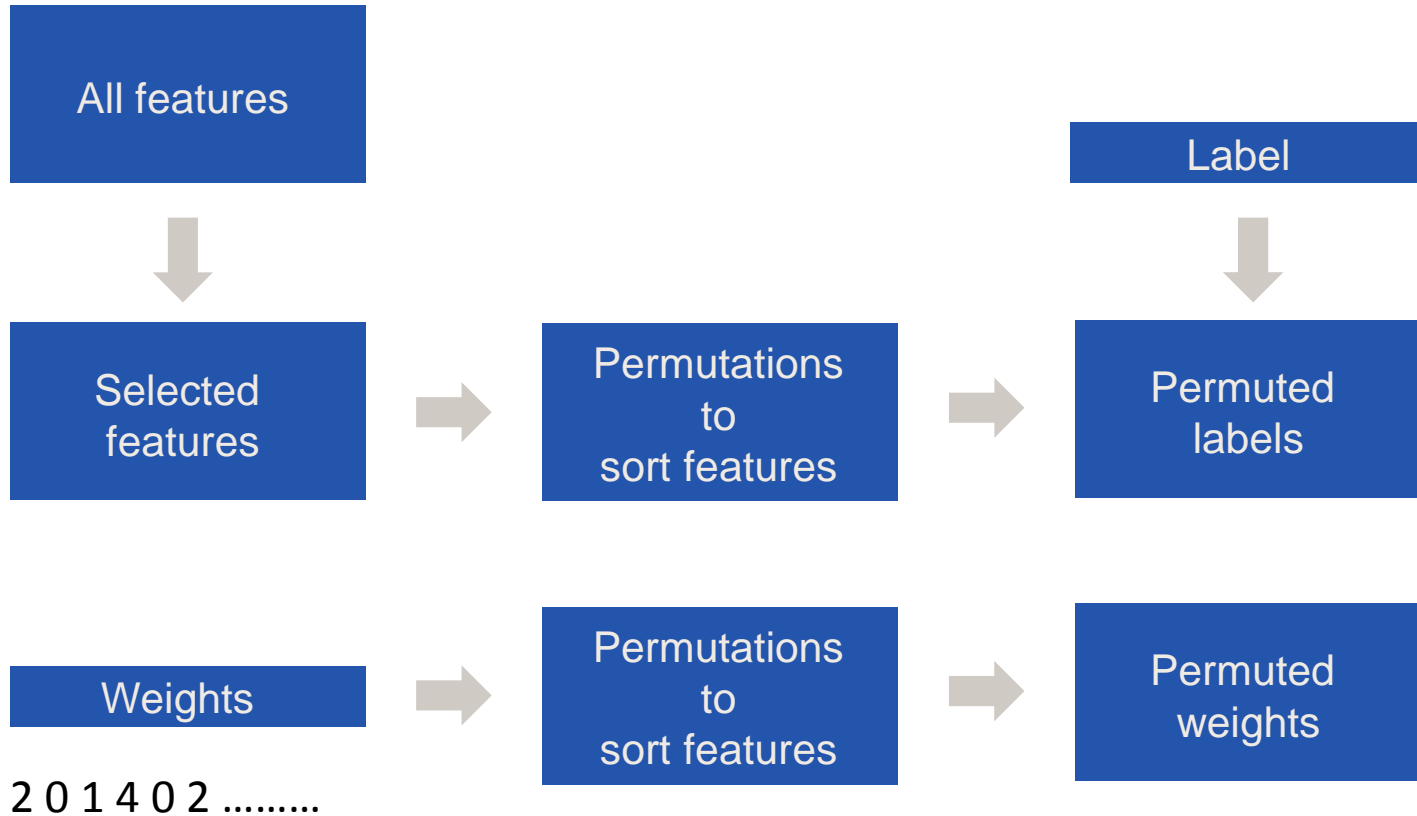
$$t_* = \operatorname{argmax} gain(t)$$

Actual implementation uses ratio information gain over split ratio

# Training Individual Trees

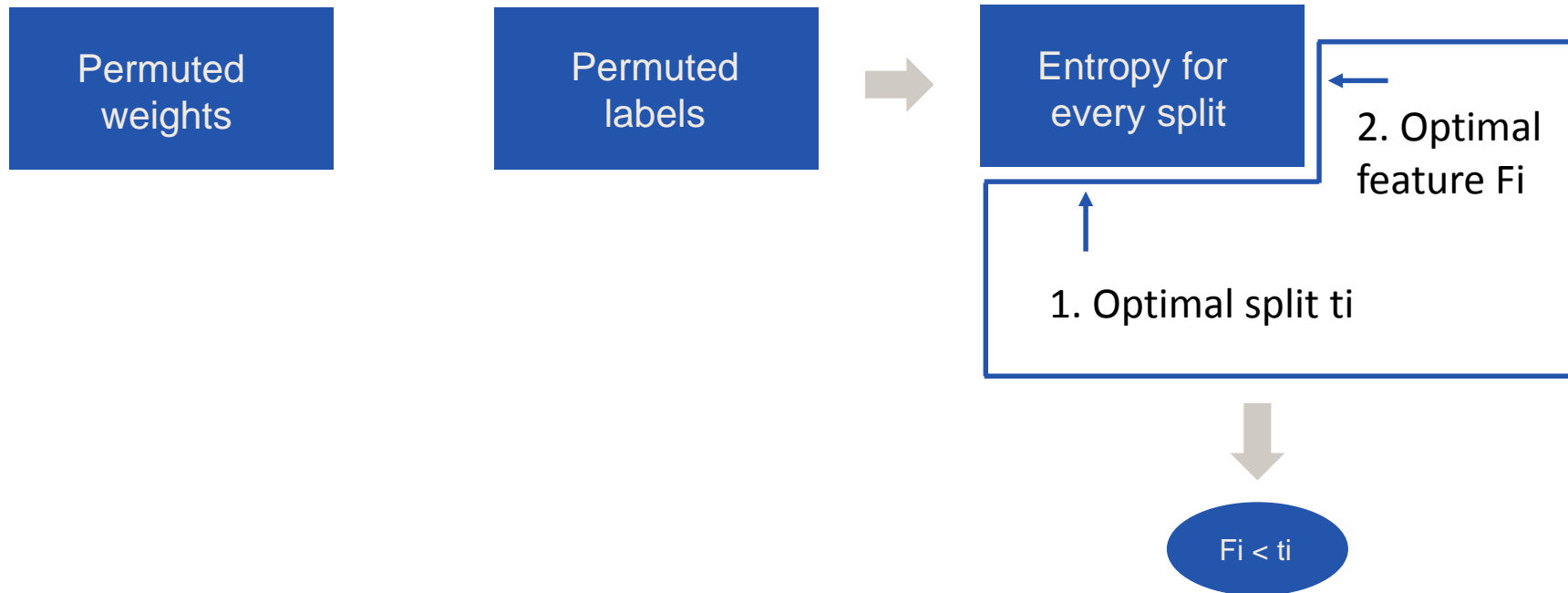


# Training Individual Trees



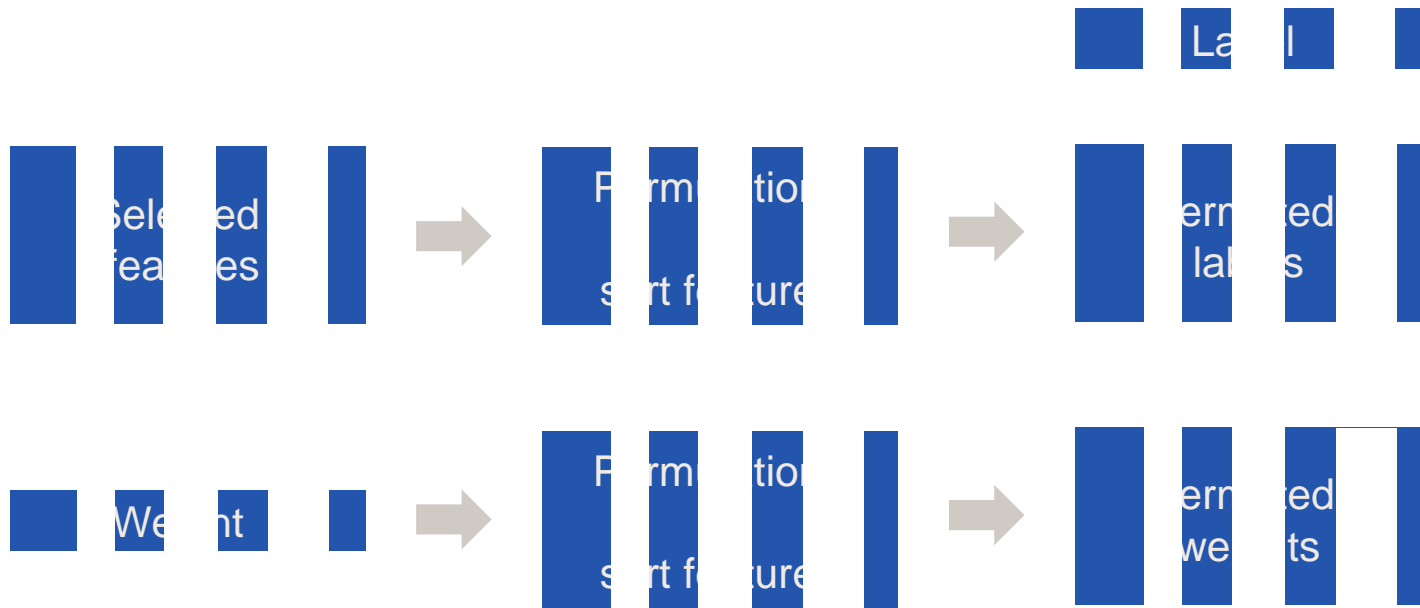
# Training Individual Trees

Entropy criterion for best feature and split



# Training Individual Trees

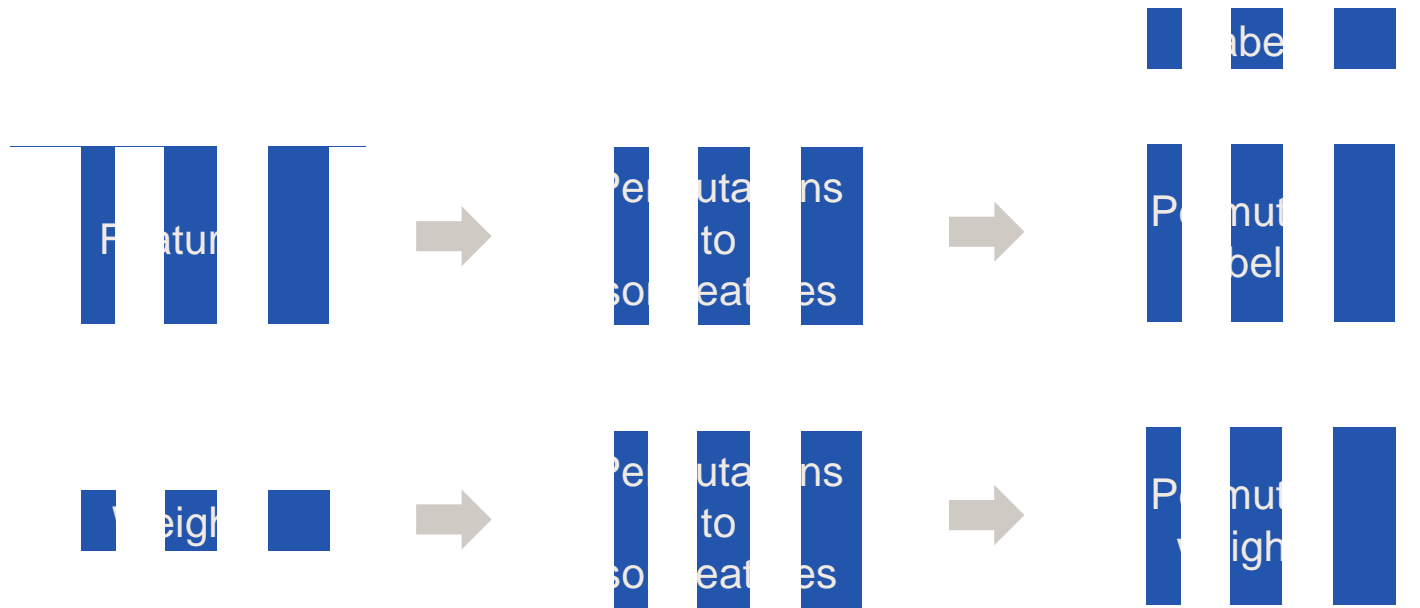
Recursively refine classification: mask data according to classification





# Training Individual Trees

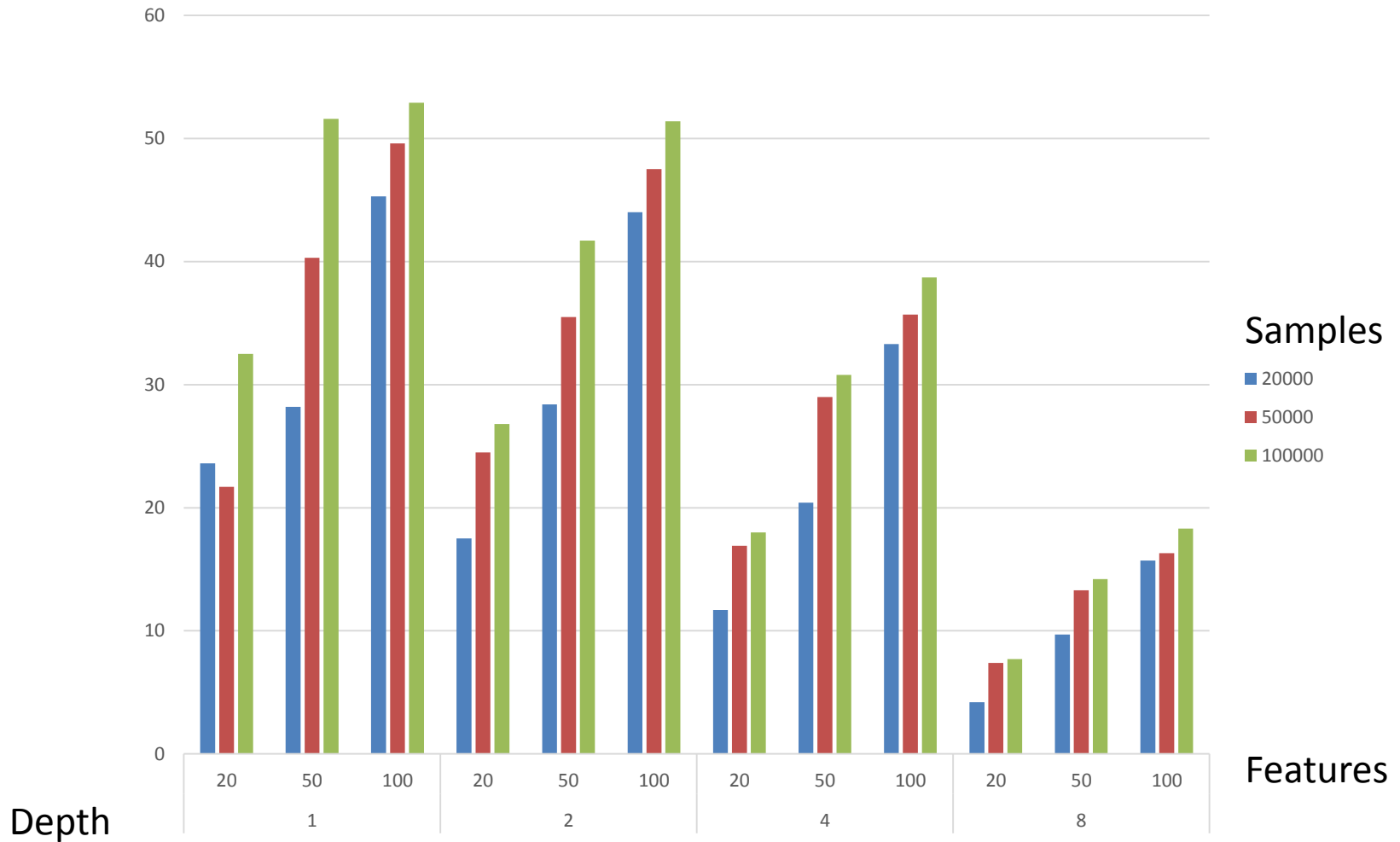
Recursively refine classification: mask data according to classification



# GPU Implementation

- Parallelism at multiple levels
  - Multiple trees, one for each set of weights
  - Independent features
  - Independent split points
  - Multiple nodes further down the tree
- GPU kernels can be implemented with standard primitives
  - Random number generation for weights
  - Parallel scan (cumulative sum)
  - Parallel map
  - Parallel reduction to find optimal feature and split

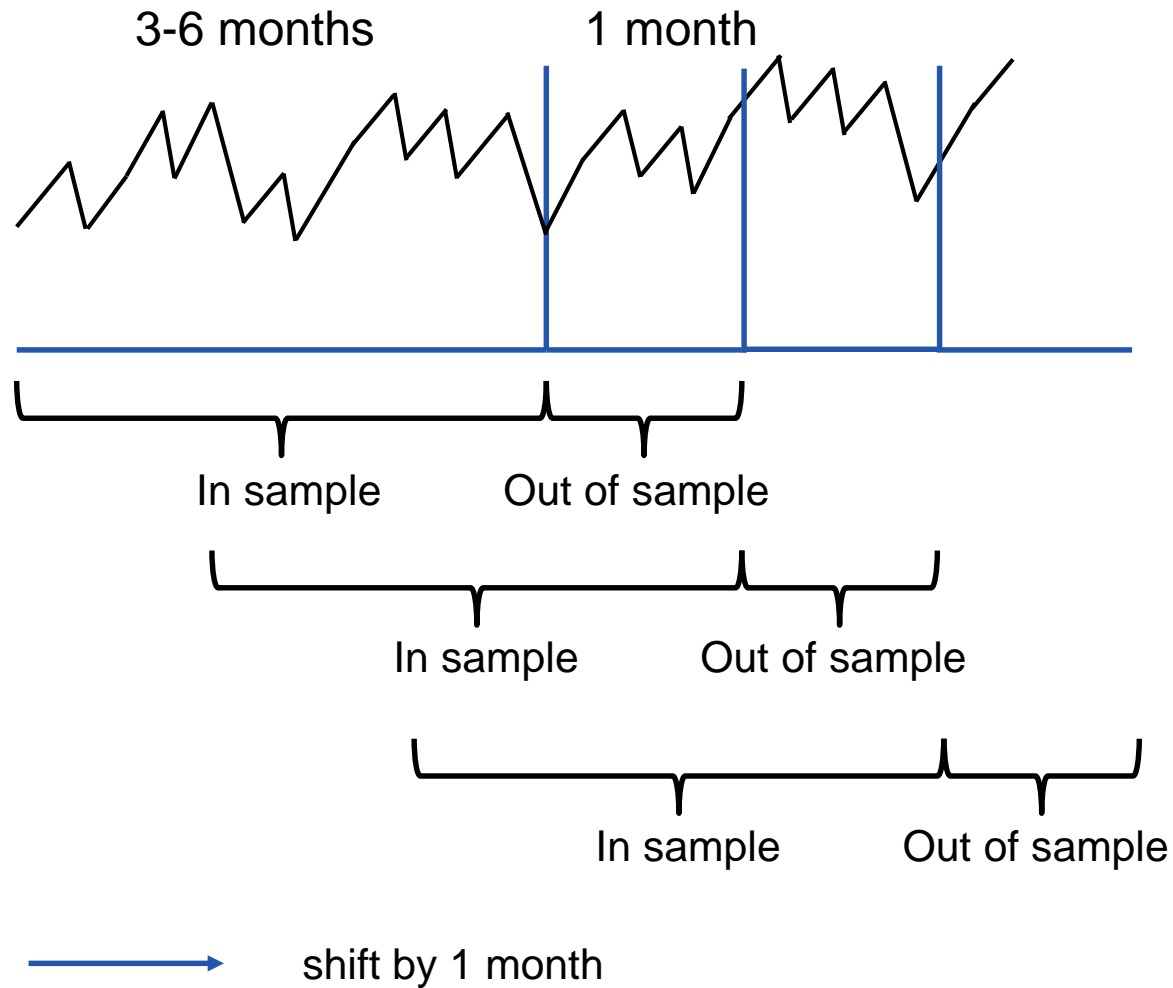
# Speedup



# Strategy Backtesting

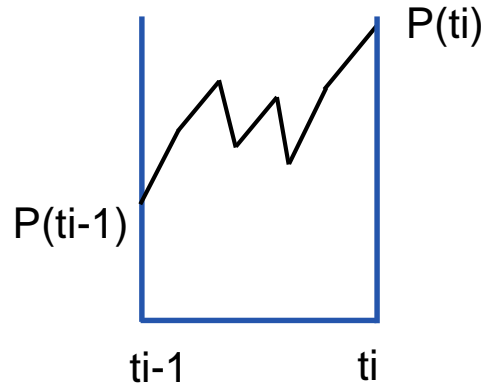
Challenge2: How to choose best trading strategy ?

# Walk Forward Optimization



# Trading P&L

Market prices



Market returns

$$r(t_i) = \log(P(t_i) / P(t_{i-1}))$$

Market returns  $r(t_i)$

..... | r | r | r | r | r | .....

Trading decision  $s(c)$

..... | 1 | -1 | 1 | 1 | -1 | .....

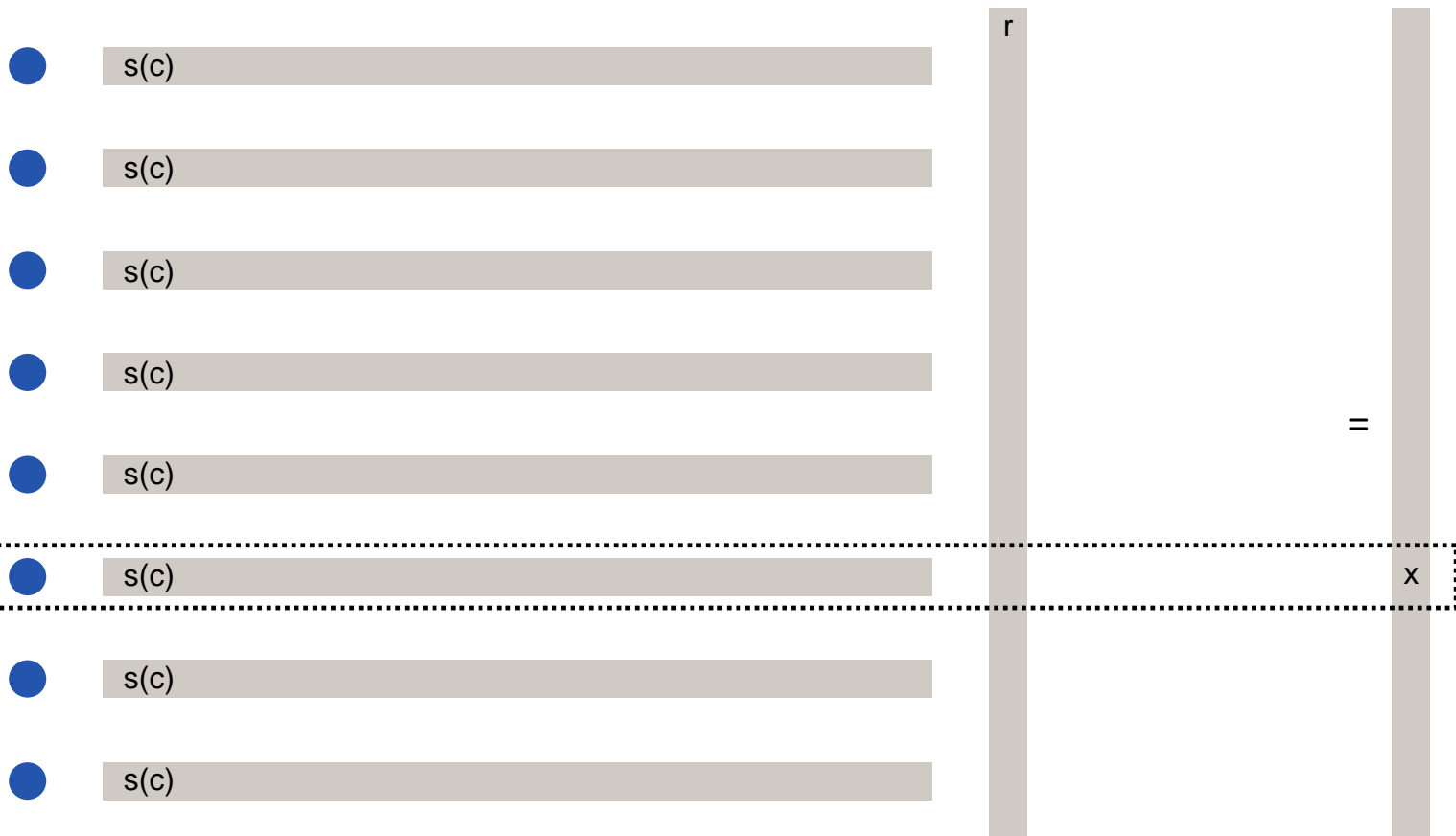
time

$$P\&L(c) = \langle s(c), r \rangle$$

# Optimal Configuration

Configurations

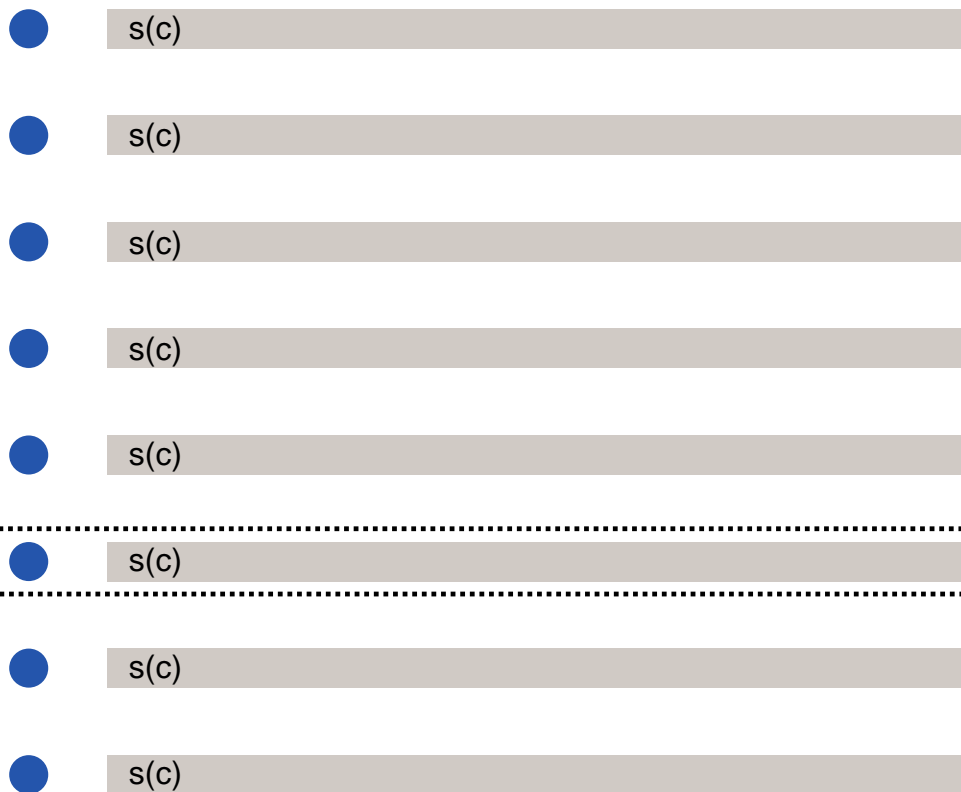
P&L



pick configuration with largest P&L

# Bootstrapping Trading P&L

## Configurations

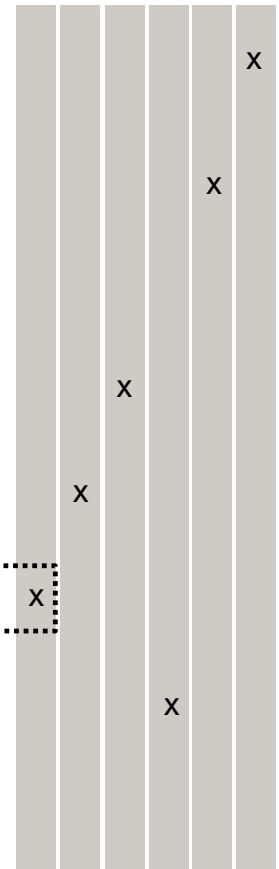


pick configuration with largest P&L

## Weights



## P&L





# Hypothesis Tests

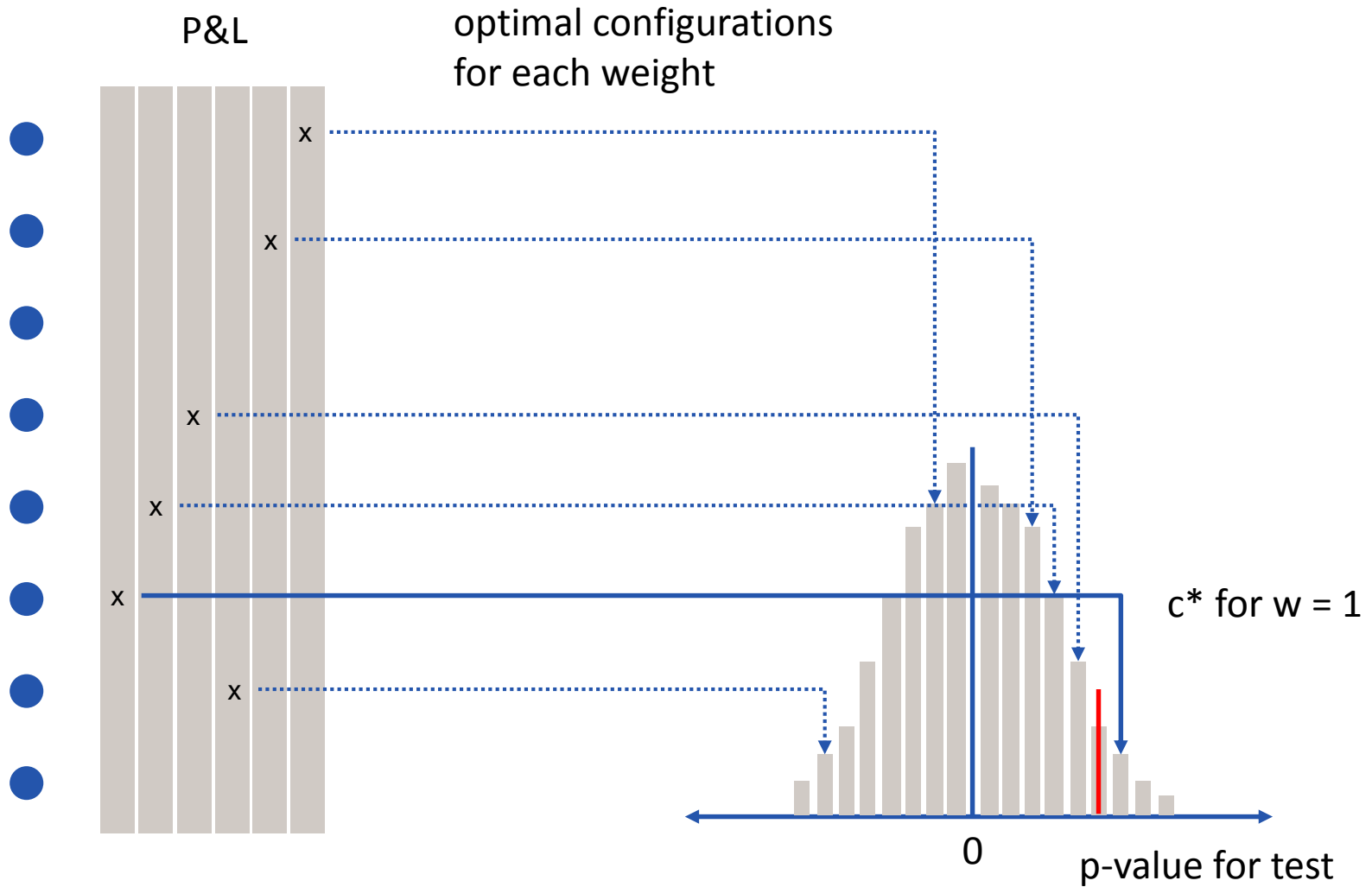
Null Hypothesis

Trading P&L  $\leq 0$

Alternative Hypothesis

Trading P&L  $> 0$

# Trading P&L Distribution

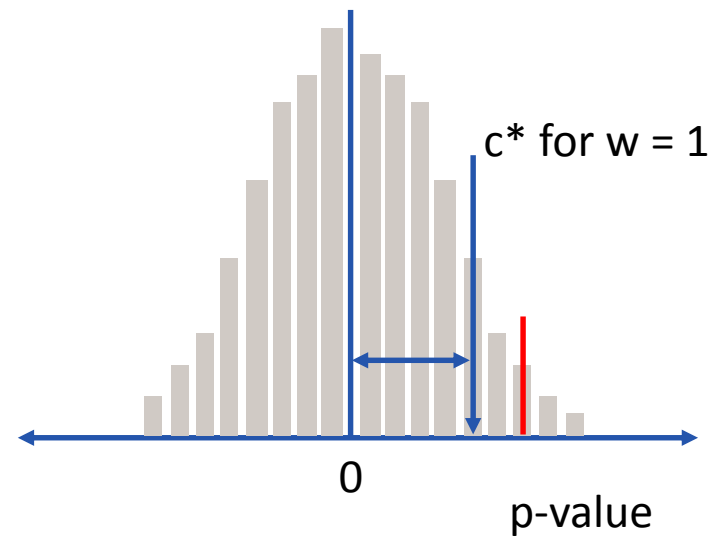
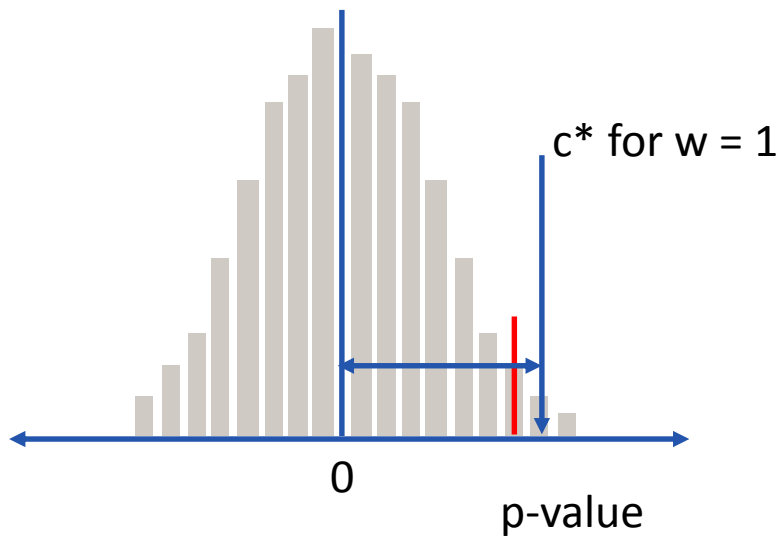


# White Reality Check

Market 1

.....

Market n



- Scale exposure according to distance from 0
- Do not trade if negative returns

# GPU Implementation

- Parallelism at multiple levels
  - Multiple markets
  - Independent in-sample / out-of-sample windows
  - Independent strategy configurations
  - Independent time steps for utility functions such as mean return
- GPU kernels can be implemented with standard primitives
  - Random number generation
  - Matrix multiplication (almost, up to return vector scaling the weights)
  - Parallel reduction

# GPU Implementation

- GPU grid
  - Multiple markets
  - Independent in-sample / out-of-sample windows
- Per GPU
  - Independent strategy configurations
  - Independent time steps for utility functions such as mean return



# Questions ?

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