

STAC Update: Machine Learning

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STAC-ML Markets (Training) Benchmark : Underway

- Existing ML training benchmarks are not *specific* to Finance:
 - They typically focus on <u>categorical</u> decisions (e.g., most probable next word)
 - Finance often requires <u>quantitative</u> models (e.g., fair value of a derivative)
- Finance use cases may require training many, many models
 - Historical backtesting may involve models specific to points in time
 - This becomes a scale-out problem vs. scale-up (e.g., LLM training)
- Many use cases have been proposed and discussed, but may not satisfy all high-level requirements:
 - Is this an ongoing concern for many end-users?
 - Can performance and quality be reliably measured and compared?
 - Can we validate that the implementation conforms to the specifications?



Some ML Training Use Cases Being Considered

Model Type / Use case	Issues / Notes
Predict prices/returns/portfolio-weights from market data	 Obviously interesting use cases Training / re-training very important Low signal-noise means models learn quickly and erratically – difficult to benchmark
Complex multi-dimensional functions (Derivative valuation, Model Calibration PDE solving)	 Also sees much current interest Not clear if training is the bottleneck for most use cases (train once and done?)
Synthetic market data generation	 Useful research and risk testing tool Quality evaluation may be difficult Again, not clear training is bottleneck
Reinforcement learning for (hedging, trading,)	 Under investigation



Training: Tell us what You think

- STAC Benchmarks are defined by financial firms to reflect their needs
- What training workloads give you the insight you need?
- Find us today to talk more, or...
- Join the Working Group!



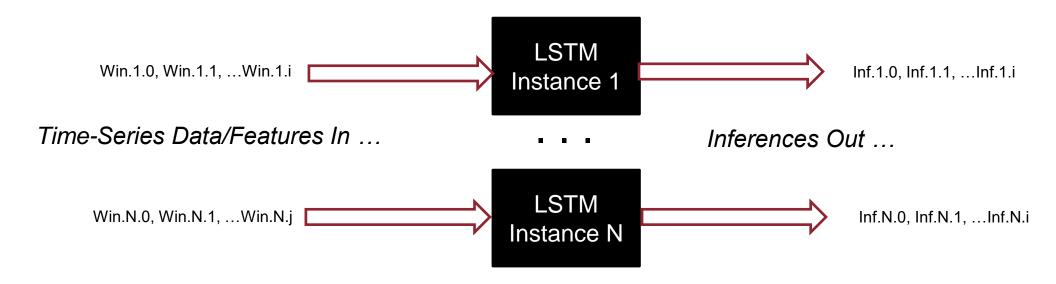


STAC-ML Markets (Inference) : Basics

- LSTM models inferring on simulated market data features
- Goal: isolate inference performance
 - Inference engine software
 - Underlying processors, memory, accelerators, etc.
 - Anything required to optimally use the former with the latter (e.g., data transfer to processor memory)
- Metrics:
 - Latency, throughput, error, power efficiency, space efficiency, cost
- Benchmarks allow any level of precision (including mixed-precision)



Benchmark Schematic; Scaling Dimensions



- Model size
 - Three are currently specified
 - Input data window scales with model size
- Number of Model Instances running in parallel
 - As specified by the SUT provider
 - Performance / efficiency per model instance is key for co-located inference



Use Cases and Optimizations

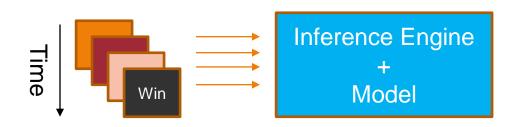
- Different Use Cases:
 - Trading Latency Optimization
 - Backtesting Throughput Optimization
- Optimization tradeoffs (latency vs throughput vs efficiency vs error) are up to the SUT provider
 - The benchmarks do not assume an inference application
 - The tests collect all metrics every time, no matter the optimization goal
 - Any quantization scheme allowed, if used consistently



Two benchmark suites

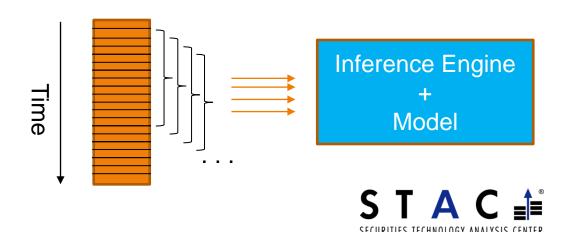
Sumaco

- Operates on fully populated, unique windows of time-series data/features
- Examples:
 - Inference over the recent past in response to an asynchronous event
 - One model may be used to reason about multiple instruments



Tacana

- Operates on sliding windows of a single time-series of data/features
- Example:
 - Inference every tick or bar
- May provide lowest possible tick-toinference latency



STAC-ML Markets (Inference) - Comparability

- The benchmark is agnostic to the architecture of the SUT and inference engine, and the precision of the computation
- Report readers can explore latency / throughput / error / efficiency tradeoffs
- STAC only allows direct competitive comparisons if all the following are true:
 - Same suite (Tacana to Tacana, or Sumaco to Sumaco)
 - The same LSTM model
 - Error results are comparable
 - SUT A can compare to SUT B if SUT A's error is strictly less than, or only slightly greater than SUT B's
 - All performance comparisons must include an efficiency comparison to provide context
 - All latency comparisons must include a throughput comparison for context



Myrtle.ai tested the Tacana Suite with FPGA as accelerator

Last year did STAC-ML Sumaco (MRTL221125) and now Tacana!

- STAC-ML Pack for Myrtle.ai VOLLO[™] (Rev B)
- VOLLO SDK 0.2.0
- VOLLO Accelerator 0.2.0
- Ubuntu Linux 20.04.5 LTS
- BittWare TeraBox[™] 1402B (1U)
 - 4 x BittWare IA-840f-0001 each with
 - Intel[®] Agilex[™] AGF027 FPGA
 - 4 x 16 GiB DDR4 @ 2666 MHz
 - 1 x Intel[®] Xeon[®] Platinum 8351N CPU @ 2.40 GHz
 - 4 x 8 GiB Micron DDR4 @ 2933 MHz (32GiB total)
- Latency-optimized, bfloat16 precision







Results highlights – Myrtle.ai

- For LSTM_A (the smallest model) the 99p latency was:¹
 - 5.07 µs 5.08 µs Across 1, 2 & 4 model instances tested (NMI)
 5.97 µs with 8 NMI
 - 6.96 μs with 24 NMI

- For LSTM_B the 99p latency was:²
 6.89 μs with 1 NMI
 6.77 μs with 2 NMI
 7.75 μs with 8 NMI
- 1. STAC-ML.Markets.Inf.S.LSTM_A.[1,2,4,8,24].LAT.v1
- 2. STAC-ML.Markets.Inf.S.LSTM_B.[1,2,8].LAT.v1







Results highlights – Myrtle.ai

For LSTM_C (the largest model) the 99p latency was:¹
 31.0 µs with 1 NMI

LSTM_A with 24 NMI achieved the following throughput and efficiency:²

 1.4M inferences / second
 1.4M inferences / second / cubic foot
 2.3M inferences / second / kW







- 1. STAC-ML.Markets.Inf.S.LSTM_C.[1].LAT.v1
- 2. STAC-ML.Markets.Inf.S.LSTM_A.12.[TPUT,SPACE_EFF,ENERG_EFF].v1