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DEEP LEARNING FOR DERIVATIVES PRICING: FROM THEORY TO PRACTICE

Tim Wood, CQF Institute, April 6th, 2021

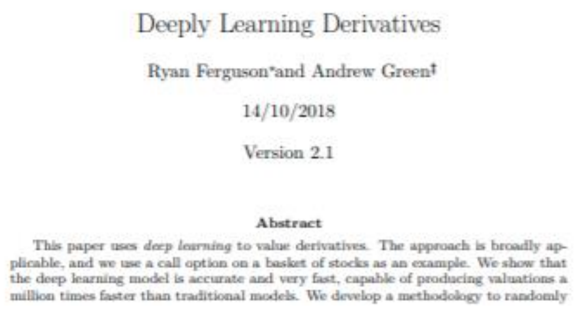
INTRODUCTION & OBJECTIVES

Who is this talk for?

- To see how and where DL may be applied to derivatives pricing and applications in risk management
- To develop an experimental framework to explore the technology and problem space
- By the end, the audience should have an idea of how-to set-up an experimental framework for themselves
- Additionally, they should have some feeling for the challenges and considerations w.r.t to applying this technique in practice
- As such will cover many topics but not in great depth given the time constraint

NO SMOKE WITHOUT FIRE?

Large and growing body of work



Deeply Learning Derivatives

Ryan Ferguson* and Andrew Green†

14/10/2018

Version 2.1

Abstract

This paper uses *deep learning* to value derivatives. The approach is broadly applicable, and we use a call option on a basket of stocks as an example. We show that the deep learning model is accurate and very fast, capable of producing valuations a million times faster than traditional models. We develop a methodology to randomly

- Deeply Learning Derivatives, Ferguson, Green, 2018
- Deep Hedging, Buehler et al, 2019
- A neural network-based framework for financial model calibration, Oosterlee et al, 2019
- Neural Networks with Asymptotics Control, Anatov et al, 2020
- Deep learning volatility: a deep neural network perspective on pricing and calibration in (rough) volatility models, Horvath et al, 2020
- Neural networks for option pricing and hedging: a literature review, Ruf & Wang, 2020

RISK AWARDS 2021

Industry Confirmation

Risk Awards 2021: new risk engine can run nearly a billion XVA calculations per second

- *“calculate, on-the fly, the impact to its book”*
- *“has given us greater visibility into our risk”*
- *“able to better exploit fleeting dislocations in the market”*

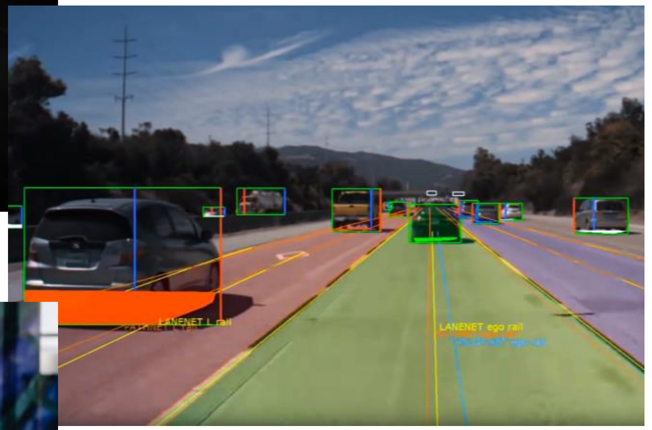
https://www.risk.net/awards/7736276/technology-innovation-of-the-year-scotiabank

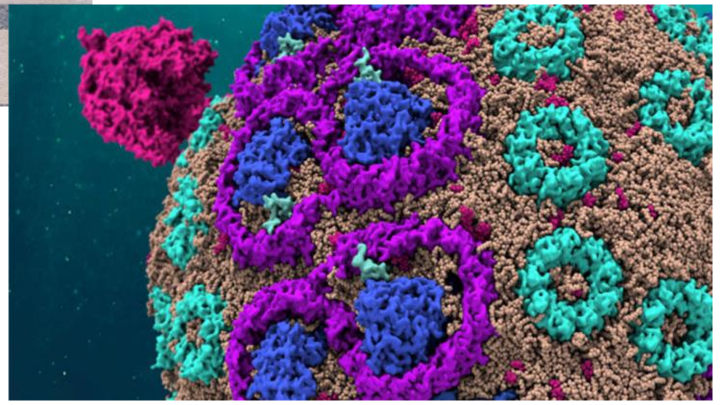
WHAT IS DEEP LEARNING ANYWAY?

Big data and plentiful compute have triggered a resurgence in AI

Deep learning and AI is impacting how we live, whether we realise it or not.

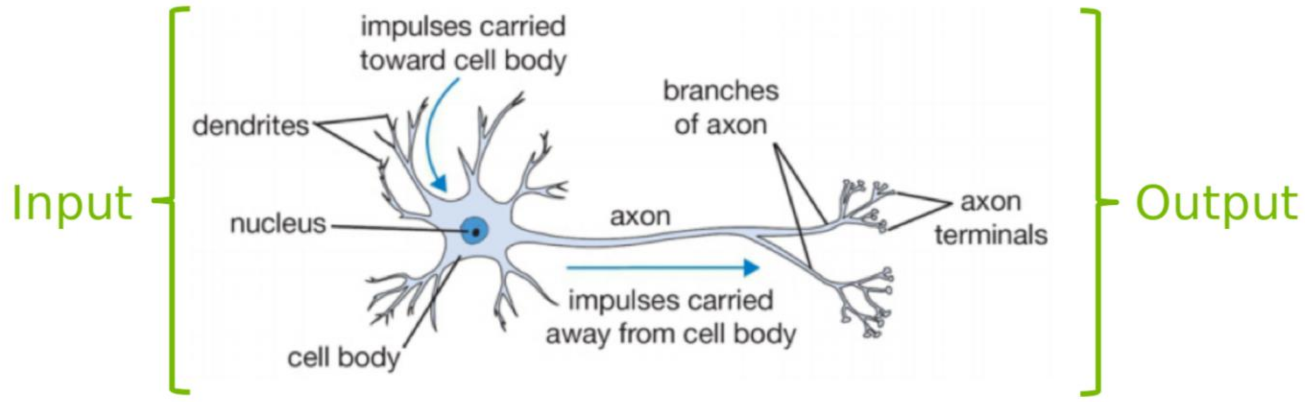
- *Recomender systems*
- *Transport: Autonomous Vehicles*
- *Smart Cities: Advanced video analytics*
- *Phara: Drug discovery*
- *Financial Services ...*

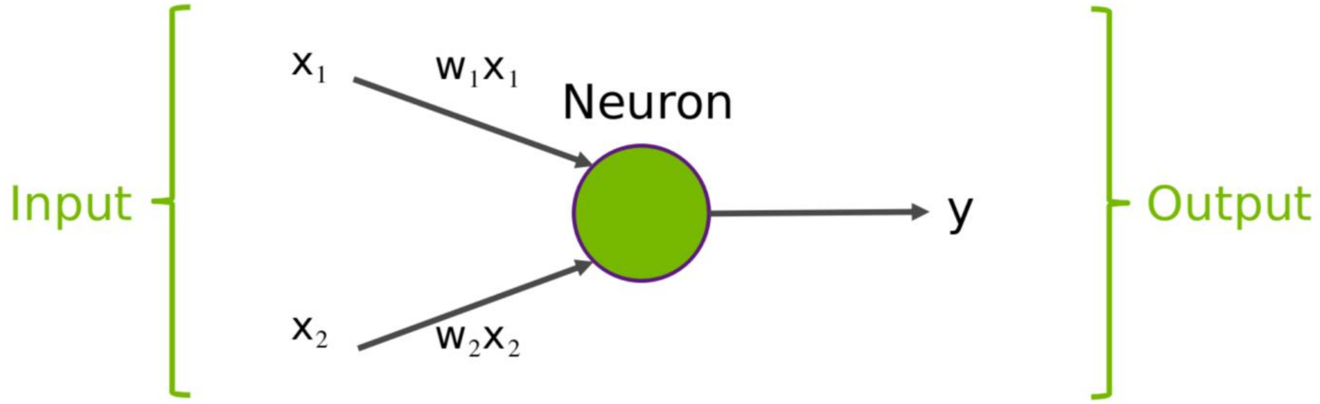




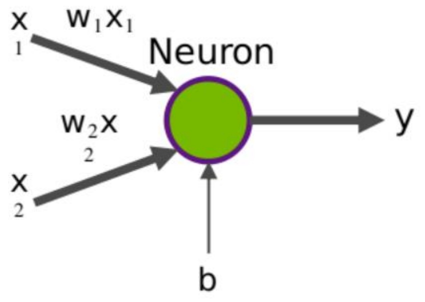
NEURAL NETWORKS

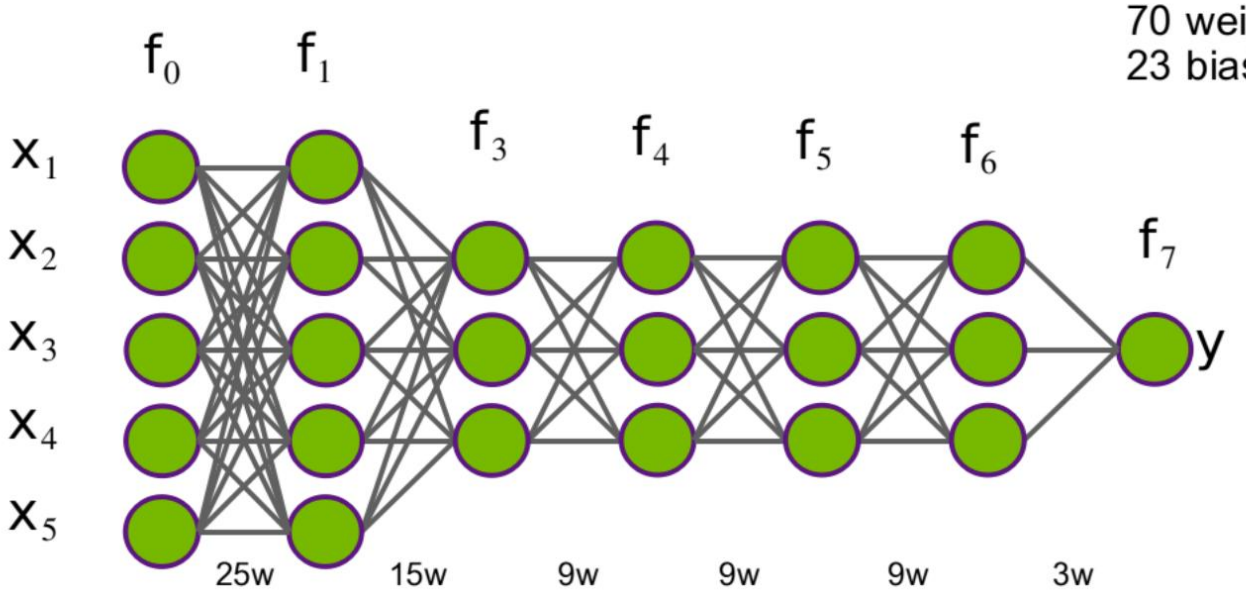
A quick refresher





$$y = f((\sum wx) + b)$$





<u>Free Parameters</u>
7 non-linear activations
70 weights
23 biases

+ the magic of backpropagation and stochastic gradient descent or other training methods

WHY ANOTHER METHODOLOGY?

Current Challenges

- *Valuation is burdonsome for all but the simplest products*
- *Traditional methods are expensive*

Can Deep Learning help?

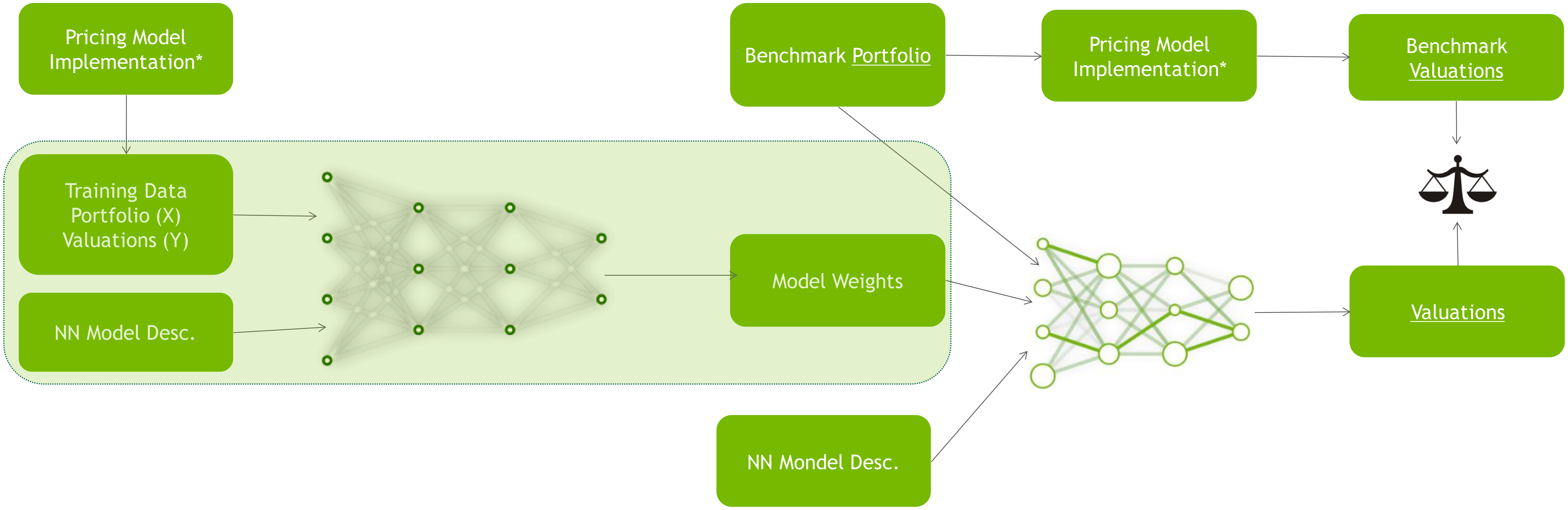
- *Expensive training, but once deployed ANNs are fast and offer very high throughput.*
- *“We can train a neural network to approximate any function to an arbitrary level of precision”*

HOW ?

- *No magic wonder model that prices all things under all conditions for all people.*
- *Much of the literature focuses on specific cases.*
- *Don’t look for a single model but instead train models for specific problems and integrate them.*
- *We already know what the computationally expensive bits are:*
  - *Optionality: Investor behavior*
  - *Market Events: Path dependency*
- *We shouldn’t throw everything away and re-invent the world*

EXPERIMENTAL FRAMEWORK

From data generation through training to benchmarking



*Same implementation displayed separately for clarity

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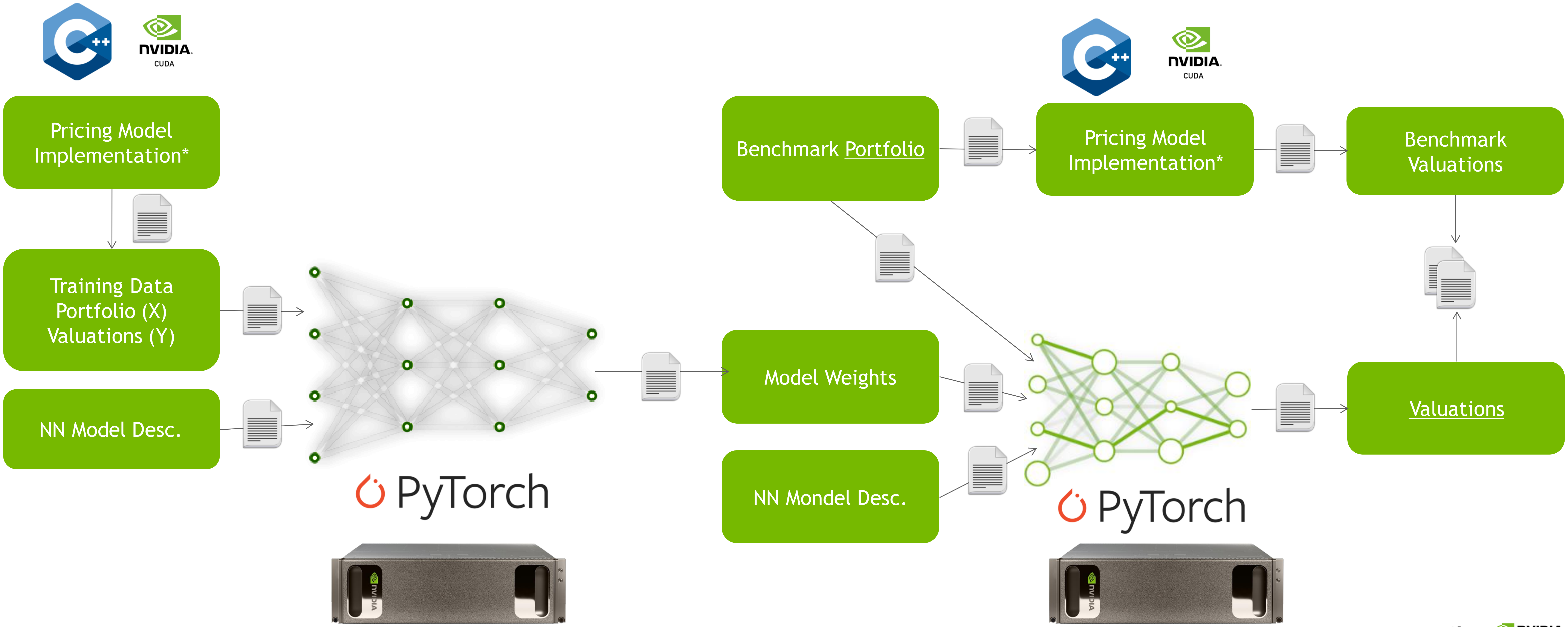

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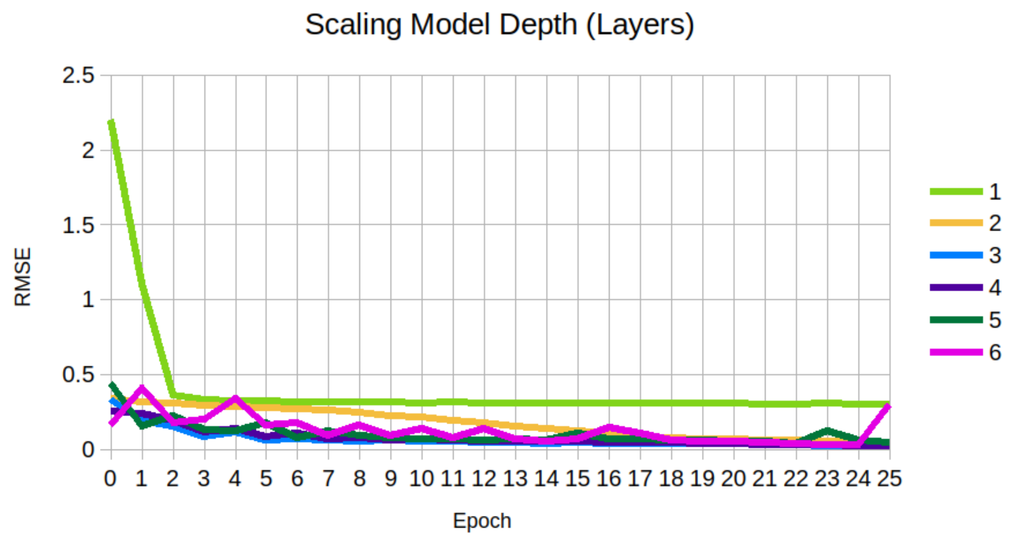
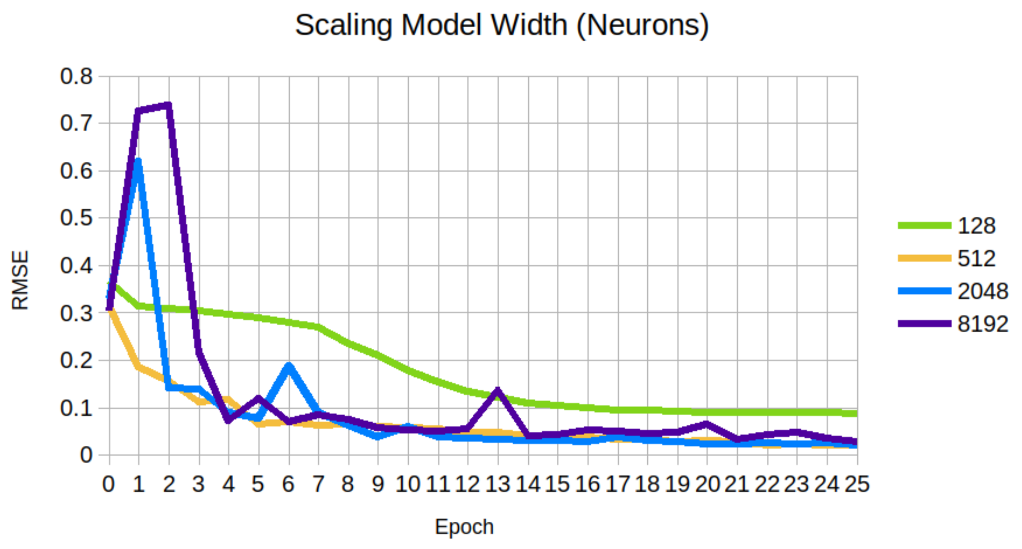
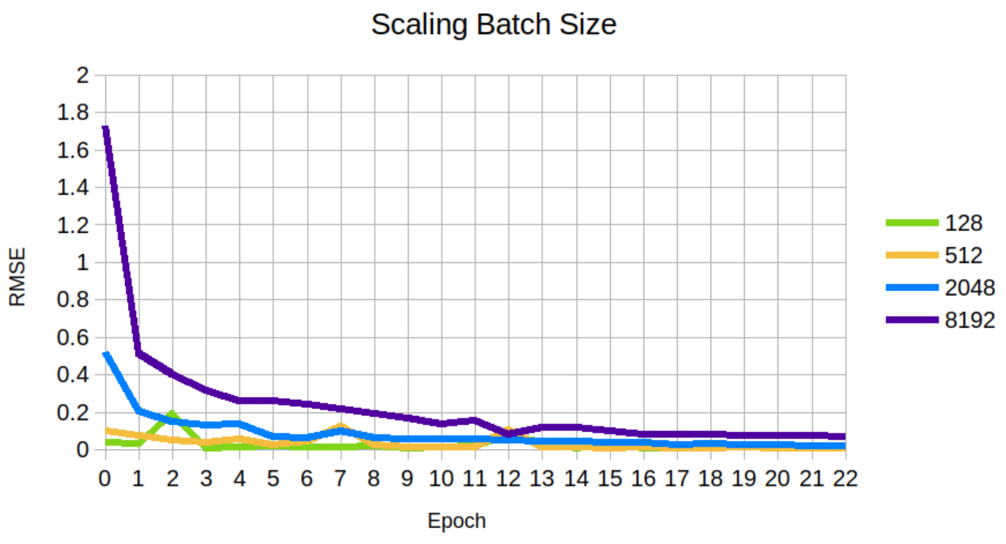
MODEL ARCITECTURE

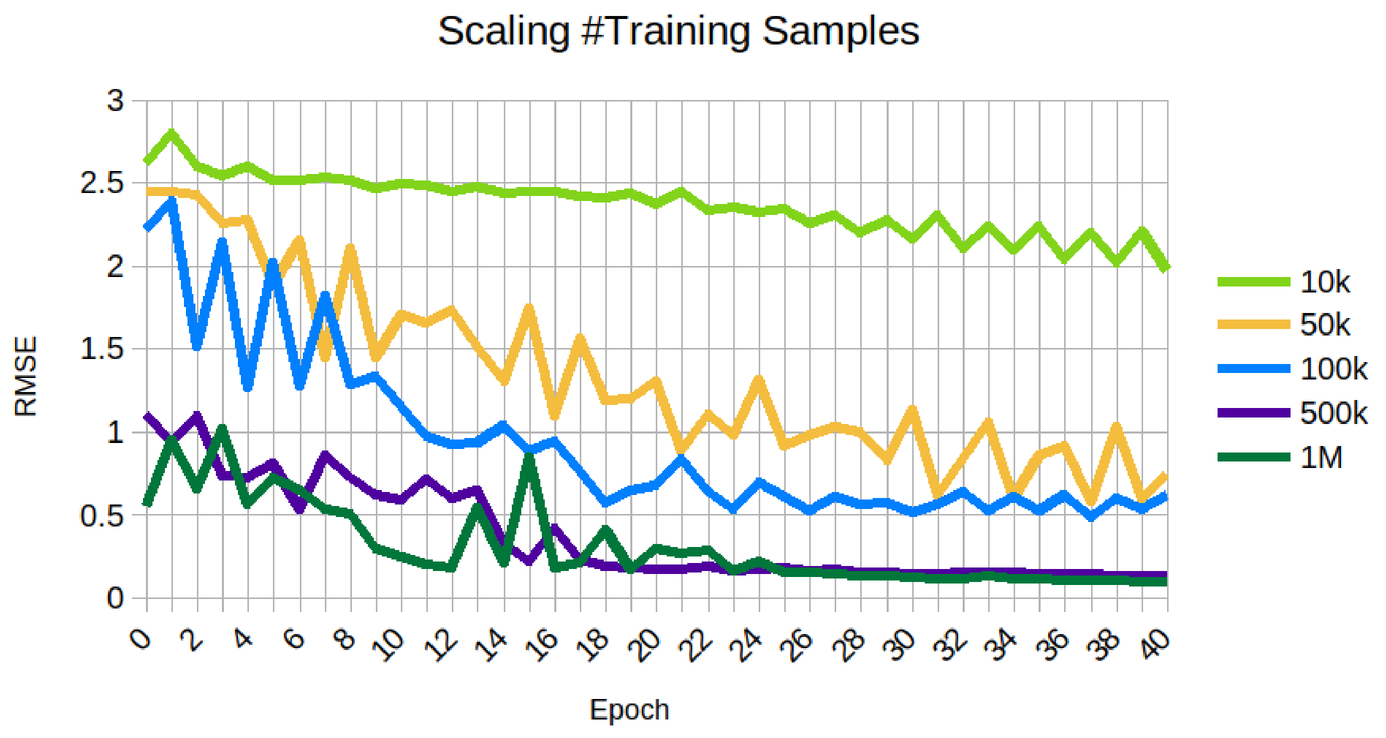


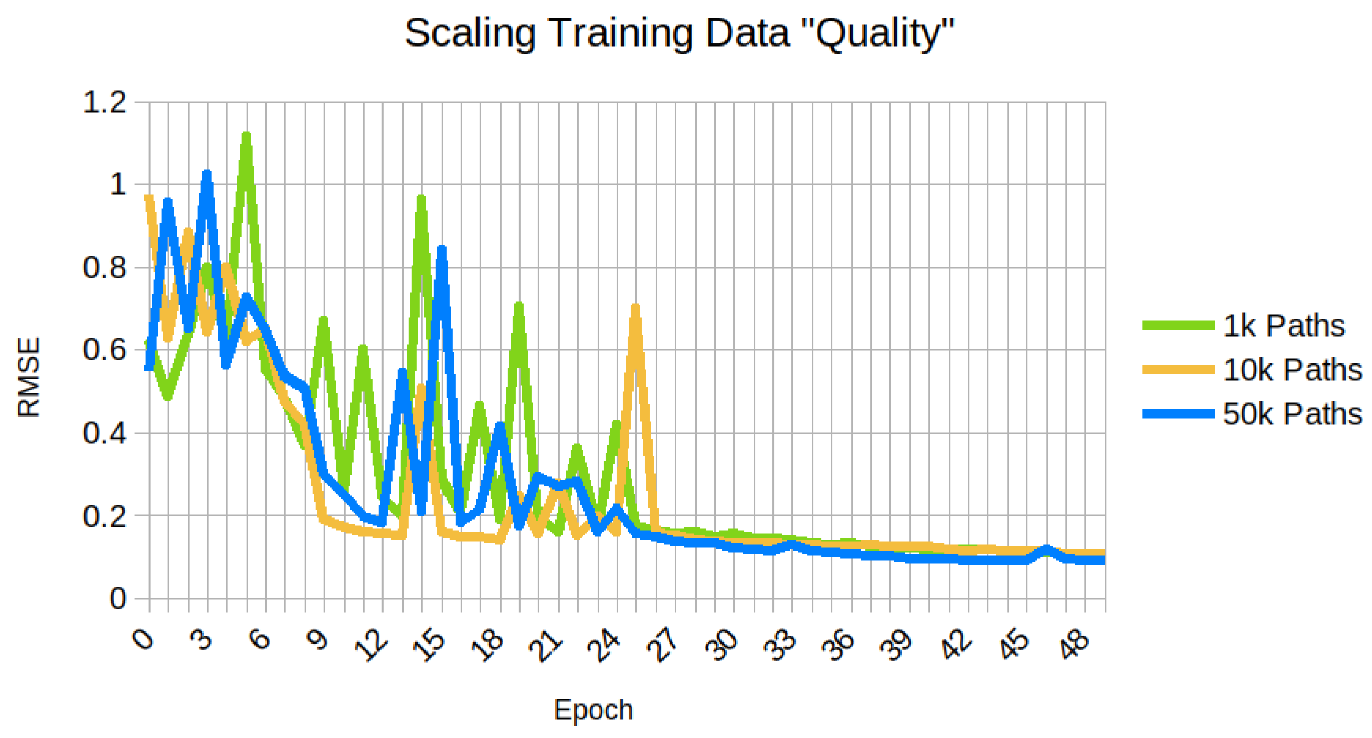




TRAINING DATA

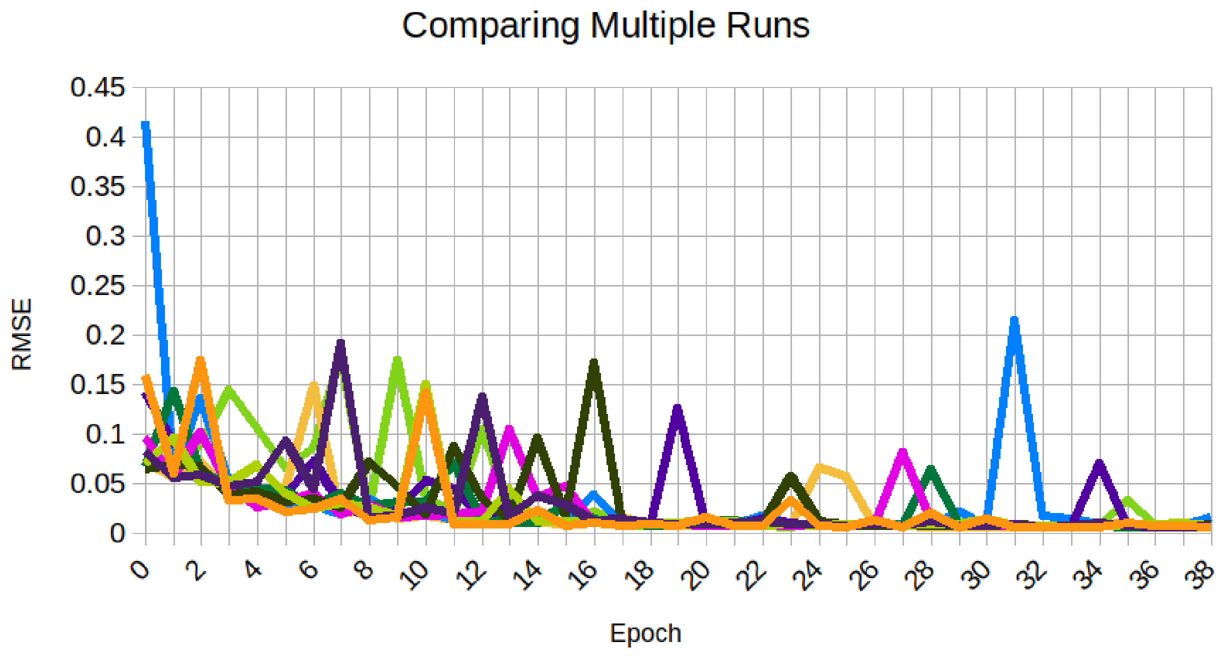
How much and how good?





INTERPRETING RESULTS

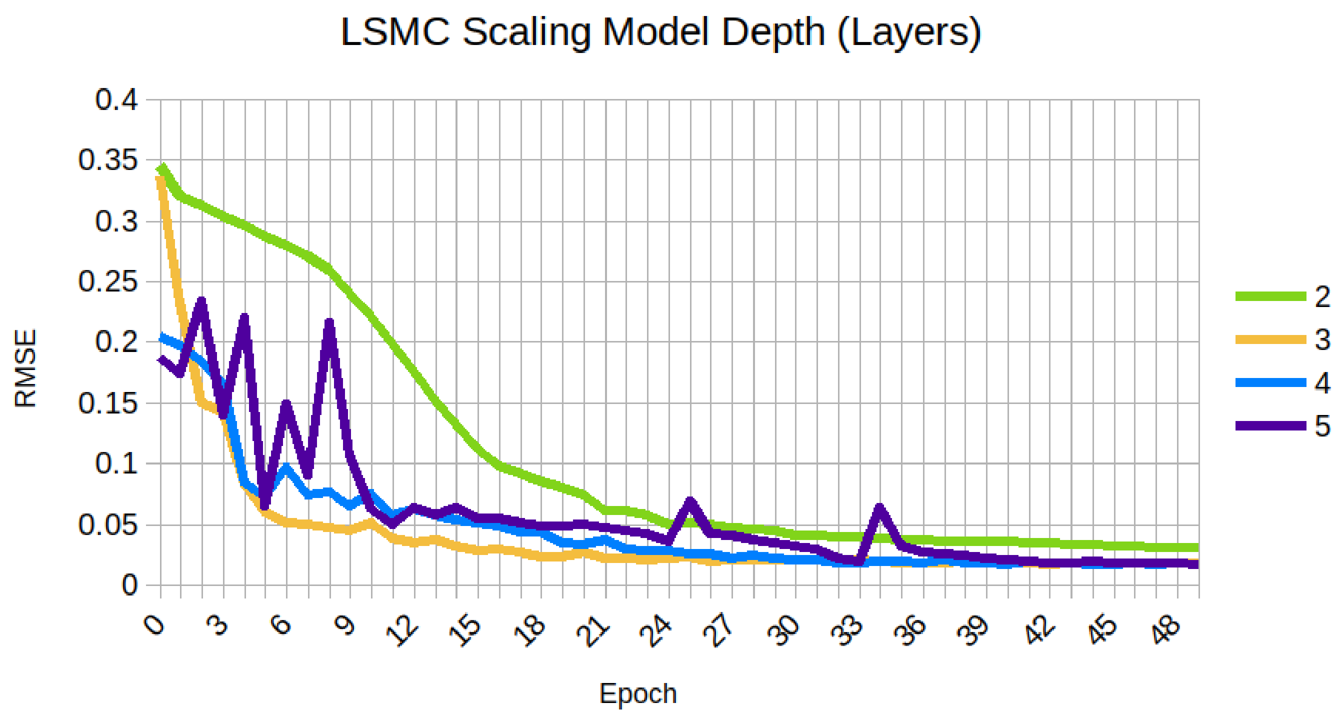
How do we know when we have a good model?

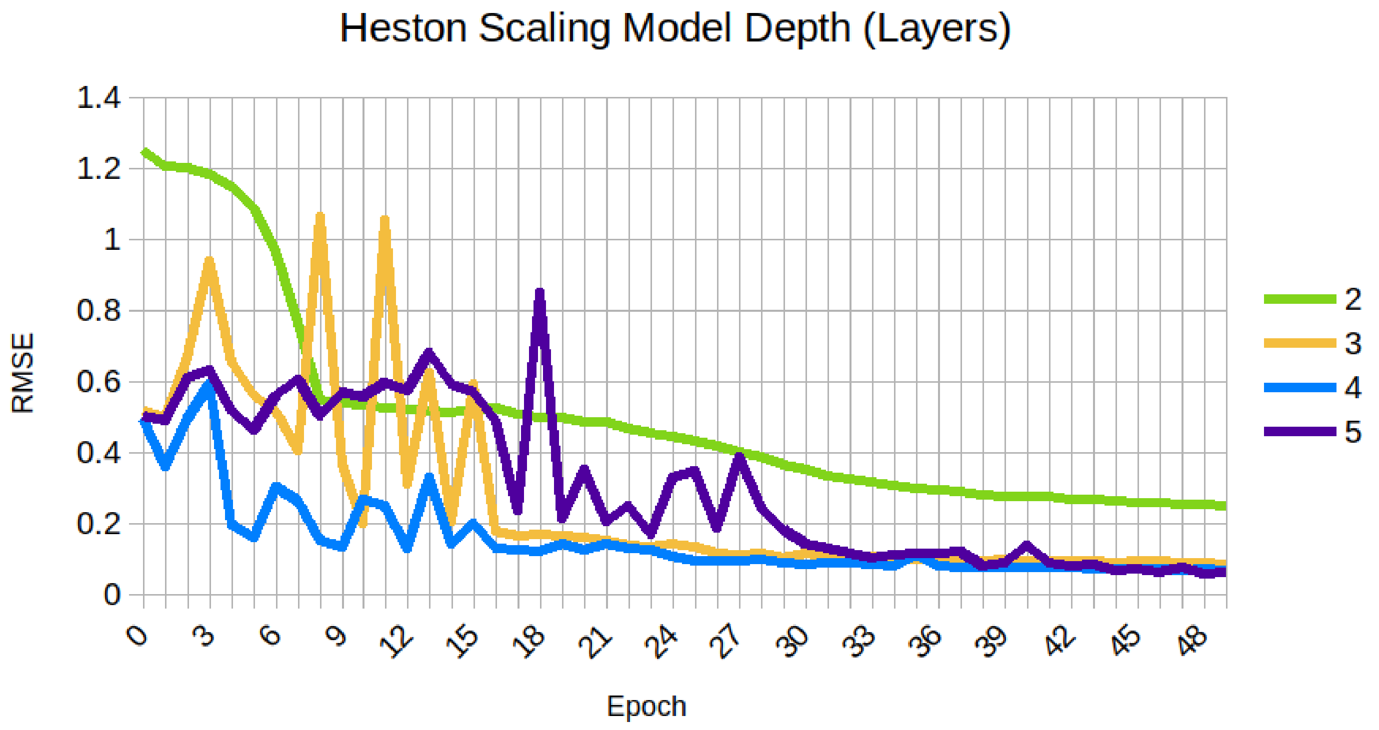


		Basis Point Difference			
S		**2.00**	**1.00**	**0.10**	**0.01**
	95.5	6,273.67	580.12	145.38	6.25
	96	5,549.74	422.24	133.34	6.11
	96.5	4,873.28	284.22	119.47	8.79
	97	4,240.59	169.74	104.16	15.79
	97.5	3,648.24	79.72	85.84	16.92
	98	3,091.33	9.25	70.53	7.43
	98.5	2,569.00	44.13	56.24	2.56
	99	2,076.98	79.28	46.26	0.03
	99.5	1,616.26	98.56	40.18	0.84
	100	1,181.41	105.52	37.62	6.14
	100.5	770.68	101.84	39.73	12.28
	101	385.15	86.18	41.88	12.10
	101.5	20.32	61.47	45.54	7.55
	102	323.90	30.27	51.93	5.40
	102.5	650.20	10.16	59.60	6.49
	103	957.36	56.15	70.91	10.27
	103.5	1,249.02	106.90	82.13	14.08
	104	1,525.05	162.70	97.78	15.56
	104.5	1,787.56	222.79	117.47	14.85
Min		**20.32**	**9.25**	**37.62**	**0.03**
Max		**6,273.67**	**580.12**	**145.38**	**16.92**
Average		**2,252.09**	**142.70**	**76.11**	**8.92**

NO SINGLE ARCHITECTURE

Each pricing model will require a new round of architecture tuning





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Riskfuel

Bermudan Swaption Pricer
Real-time valuations and risk sensitivities

Contact: sales@riskfuel.com

Visit Website

Download our Benefits Guide

Traditional valuation models of the Bermudan Swaption use numerical methods which are very costly to compute. Riskfuel models use machine learning to learn an analytic representation of the target model. The result is fast and accurate valuations and risk sensitivities.
Learn more about the Bermudan Swaption Demo.

Run Query

Send Random Batch

Trade Parameters

Strike

-2 5 1.5

Non Call Period (years)

0.5 2 1

Swaption Term (years)

Valuation Date (dd/mm/yyy)

05/04/2021

Start Date (dd/mm/yyy)

29/03/2021

Side

Pay

Pricer Results

Toggle Style

Clear All Results

Trade Valuation Comparison: 0

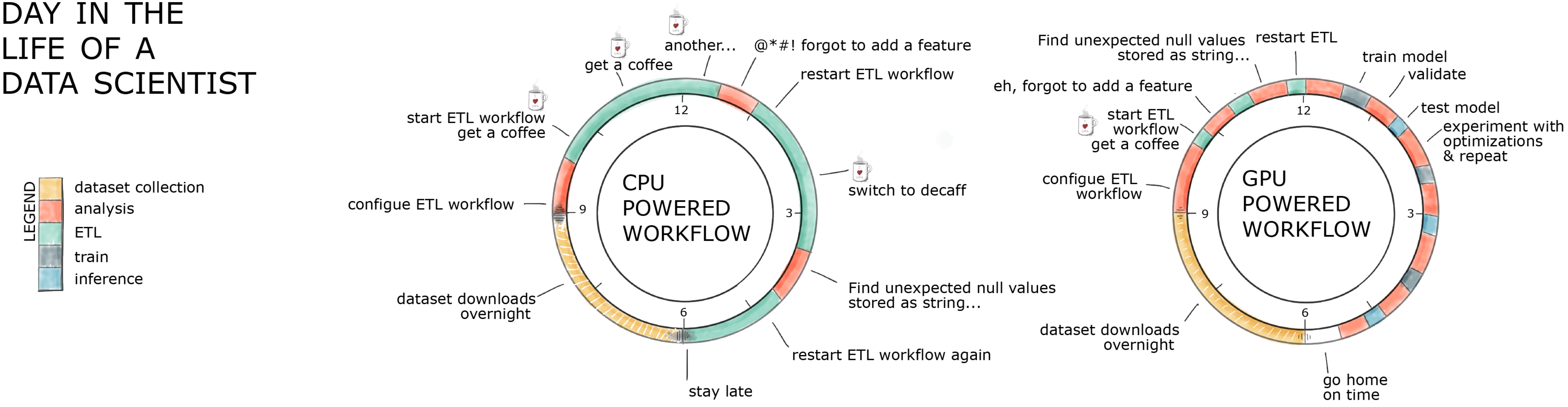
View Trade Inputs

Riskfuel	QuantLib
Value: **116.1bps**	Value: **116.4bps**

EXPERIMENTATION

Accelerated compute yields drastic productivity improvment

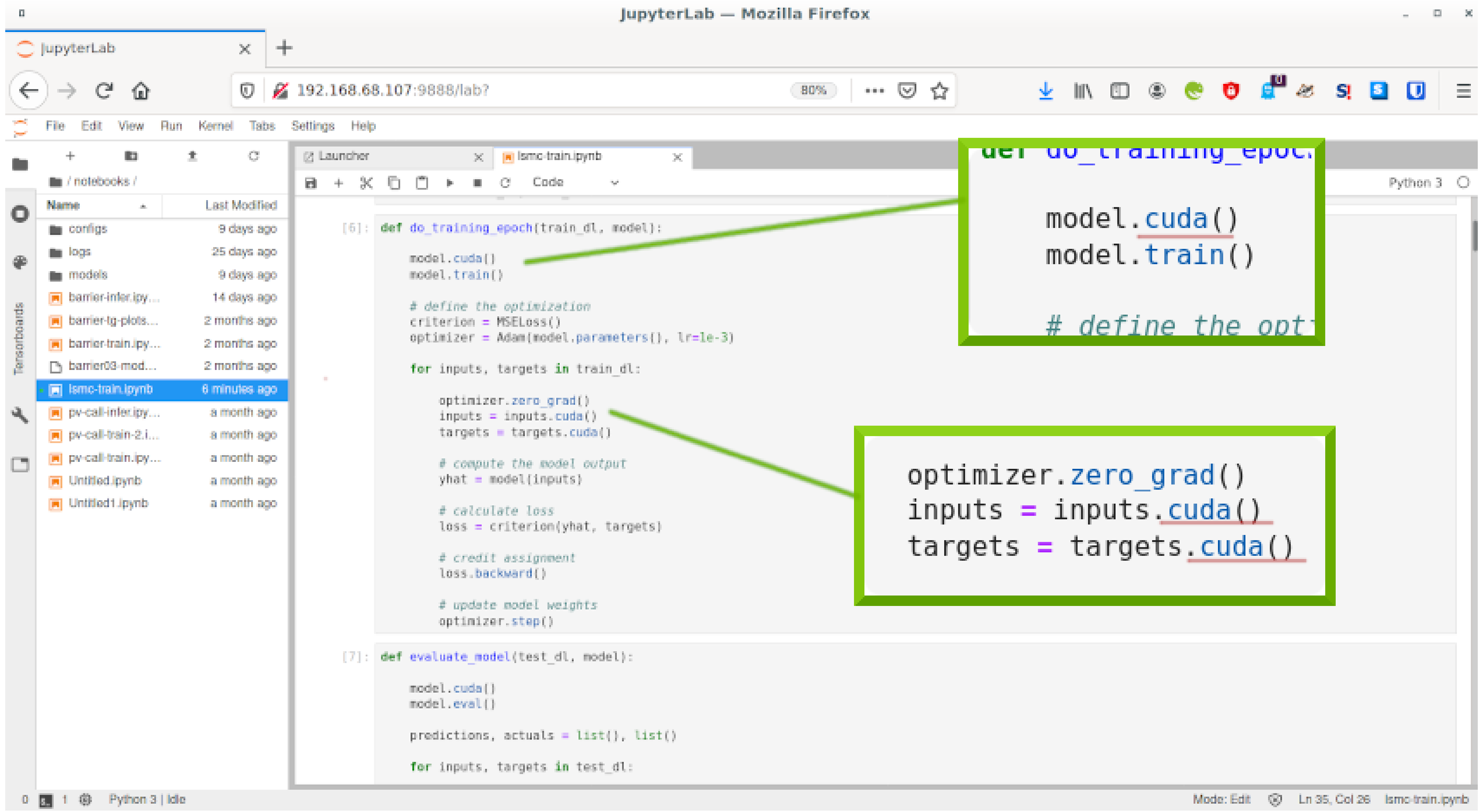
DAY IN THE
LIFE OF A
DATA SCIENTIST



TRIVIAL ACCELERATION

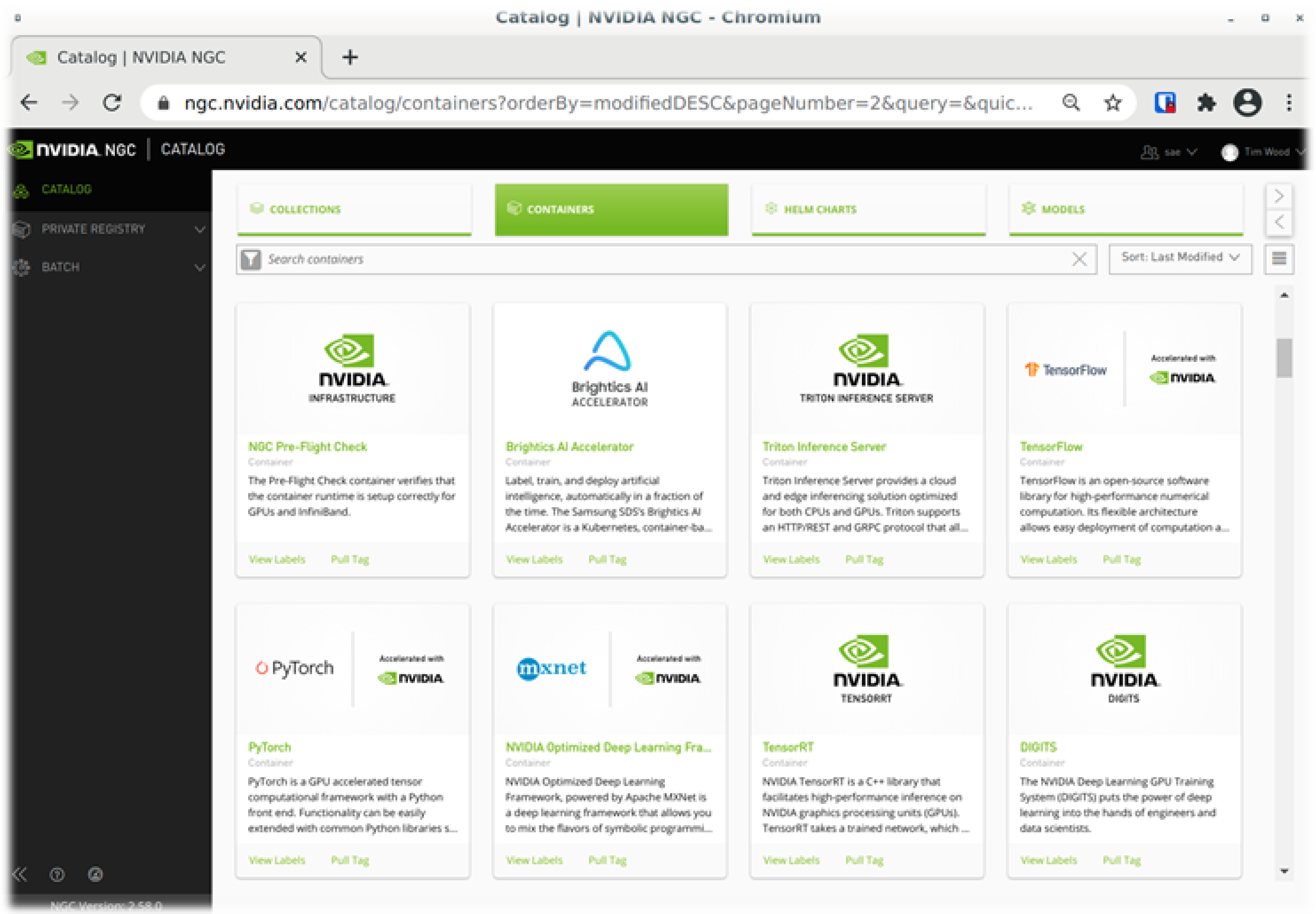
A huge performance boost with almost no effort at all

- ANNs map well to parallel architectures
- ANN training and inference workloads exhibit a high degree of trivial parallelism
- All major deep-learning frameworks have been ported to leverage the vast compute available on GPUs
- Pytorch `DataParallel` further facilitates easy scaling across multiple GPUs



NVIDIA GPU CLOUD

- Low barrier to entry
- Instant productivity
- Continuous functional and performance improvments
- https://ngc.nvidia.com/



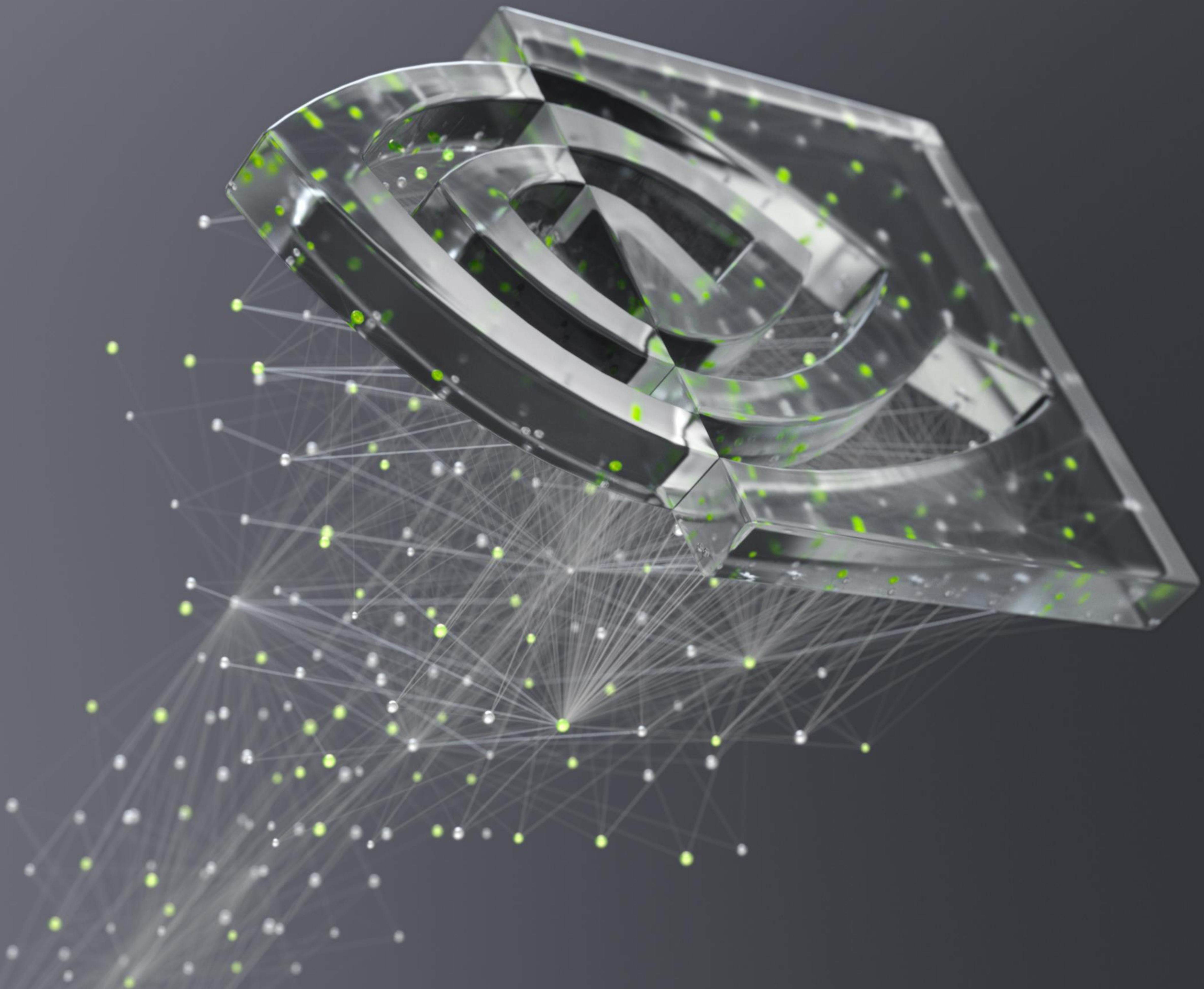
THE ROAD TO PRODUCTION

What challenges or considerations await us?

- Regulators
  - Regulators encourage technology driven innovation including the responsible deployment of machine learning and artificial intelligence.
- Validation
  - To satisfy internal and external validation and audit requirements we should anticipate a strong requirement for reproducibility through the model development cycle.
- Integration
  - Ultimately, our trained model needs to find its way to production in a controlled way. Transition from experimental environment with controlled deployment and versioning.

IN CLOSING

- By recognising the work of Scotiabank and Riskfuel, Risk.net have confirmed the emergence of Deep Learning as an applicable and valid methodology in derivatives valuation.
- Rather than a revolution, Deep Learning provides a valuable addition to the Quant’s toolbox. Existing methods and investments are not discarded but remain highly relevant.
- Apart from operational relief Deep Learning, can open the door not only to better performance but also better modelling.
- Far from being esoteric, Deep Learning has already been commoditized in the form of high quality, freely available frameworks.



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