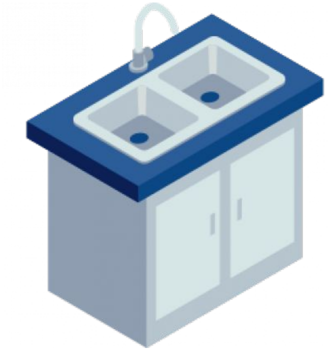
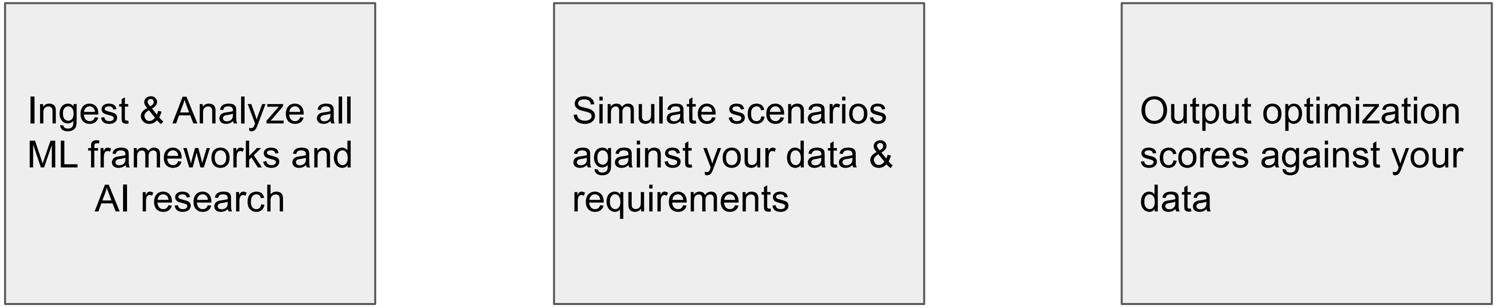


verMan.io Pitch

What we do



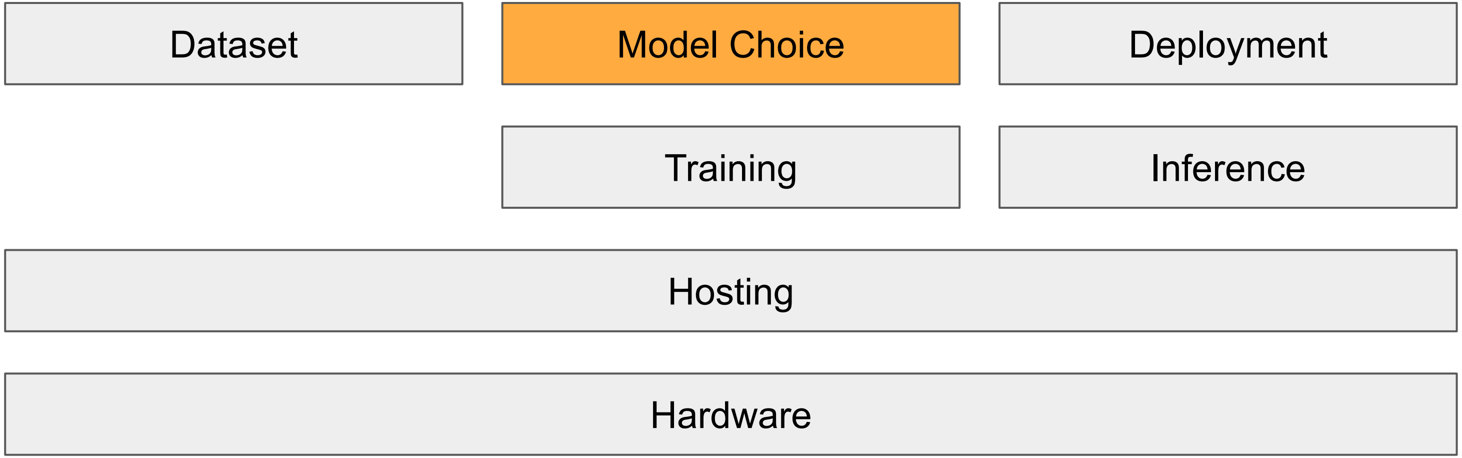
Ingest & Analyze all ML frameworks and AI research

Simulate scenarios against your data & requirements

Output optimization scores against your data

AI industry provides benchmarks against generic data
KitchenSink.ai provides optimizations against your data

Optimization techniques



Dataset

Model Choice

Deployment

Training

Inference

Hosting

Hardware

We solve model choice and 3rd-party integrate the rest

Optimization critical to make AI deployment economical

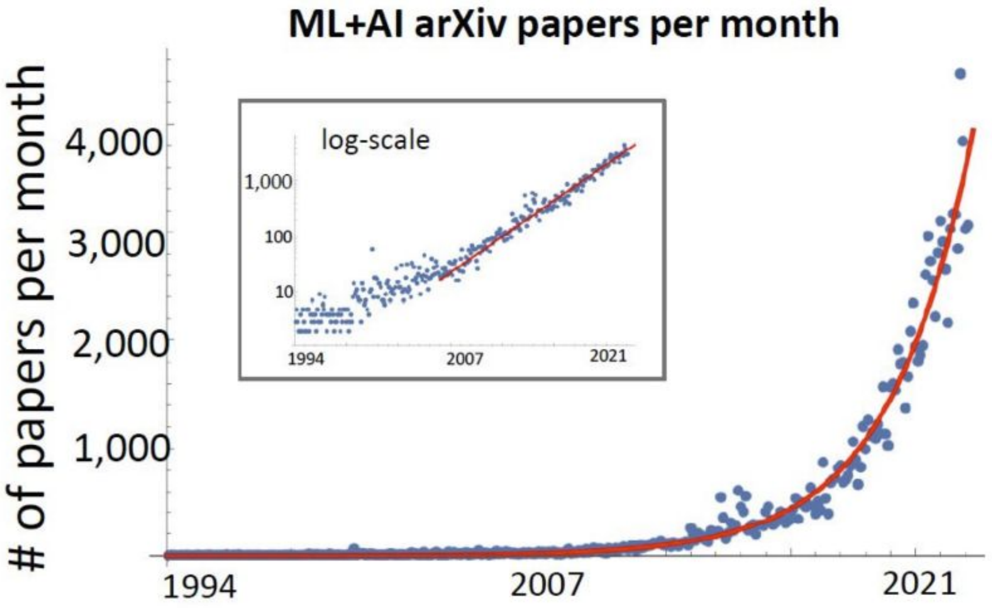
Optimizations can dramatically reduce AI deployment costs

[Need data here]

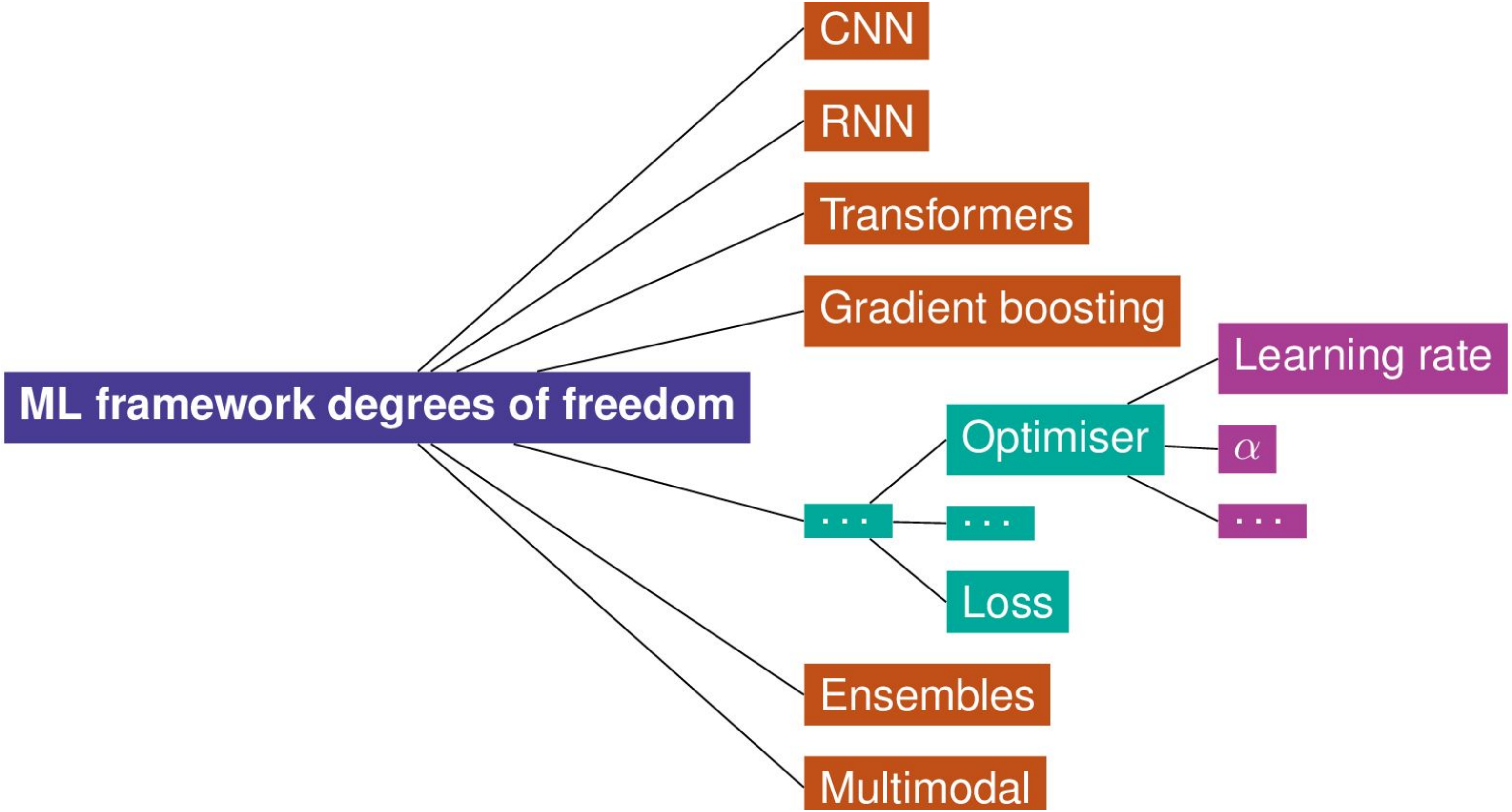
Chart showing cost impact of optimizations

Endless pipeline of emerging AI research

- [AI state of the art changing rapidly]
- Nearly impossible to analyze and interpret the volume of incoming AI research
- Examples of emerging methodologies []



Wide range of optimizations


ML framework degrees of freedom

CNN

RNN

Transformers

Gradient boosting

· · ·

Optimiser

Learning rate

α

· · ·

· · ·

Loss

Ensembles

Multimodal

No existing tools allow individualized optimizations at scale

- Economic and performance benefits are unlocked when models optimized against individualized requirements
- Currently, models largely evaluated through leaderboards, which provide a small number of arbitrary benchmarks
- Large organization can run internal bake-offs between models, but this is time consuming

Table of existing options

SQL: find best models

```
SELECT model.model_name

FROM Finished_Experiments

WHERE metrics.accuracy > 95.54

  AND dataset == “mnist”

ORDER BY metrics.accuracy;
```

SQL: find cheapest / low-resource models

```
SELECT model.model_name

FROM Finished_Experiments

WHERE metrics.accuracy > 90.54

  AND dataset == “mnist”

  AND model.parameters < 15M

ORDER BY metrics.accuracy;
```

SQL: experiment to find best models

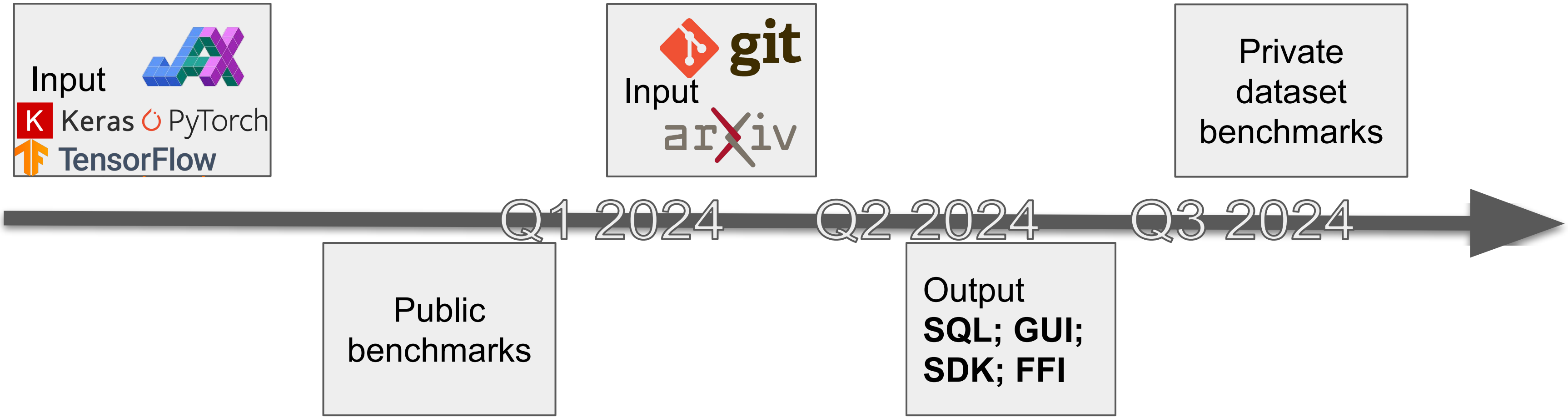
```
SELECT *

FROM Models, Optimizers, Loss

WHERE models IN top_models;
```

^ This output can be fed into a distributed trainer like MLflow and distributed hyperparameter/parameter tuner like Google Vizier, Microsoft NNI, or Ray Tune.

KitchenSink.ai Roadmap



Input JAX

Keras PyTorch

TensorFlow

Public benchmarks

Q1 2024

Input git arXiv

Q2 2024

Output

SQL; GUI; SDK; FFI

Q3 2024

Private dataset benchmarks

Mission: service that continuous/frequently determines accuracy and cost for different ML models; enabling enterprises to tradeoff accuracy and cost (and acquire SOTA for both)

Team

Samuel Marks, PhD

Finishing off his second PhD in Computer Science (compilers, AI), Samuel was running a software-engineering consultancy for the past decade. He is a top 10 contributor to Keras, and has optimised vector allocations at the C++ level for both TensorFlow & PyTorch. He is also a Google Developer Expert & a Research Fellow at Harvard.

HARVARD MEDICAL SCHOOL

THE UNIVERSITY OF SYDNEY

Sydney and Sydney Eye Hospital

Mass General Brigham
Mass Eye and Ear