Practical Tips for Managing ML/DL Experiments

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Disclaimer: The master theme for this presentation is borrowed and edited from DM theme.

Introduction

What is this talk about?

- Every research project, Has a a practical/development/engineering side.
- For our work, we need to implement and run our ideas and to check if they work!
- However, since we might not have engineering skills, we might not use software engineering disciplines or utilize the tools developed for our work.
- This might will come back and haunt us later!

What is this talk about?

- Many PhD students/researchers just want to have a working code and once they get the results, they think they are done!

- The reason? The way we work:
  - We start implementing a code and edit/debug the code until it works.
  - Once we get the result, we are done. No reason to continue.

- This is wrong:
  - You will work with this code later (rebuttal/when writing PhD dissertation, etc ….). You should be able to edit the code quickly and get new results.
  - You have a responsibility to publish your code so others can use.

What is this talk about?

- In this talk. We discuss:
  - What should we do during implementation/running/reporting phases?
  - Some guidelines/best practices for each phase
  - Tools that are helpful for our research.

Implementation Phase

What we do

- Write a working code locally.
- Debug until it works for a scenario.
- Backup: by copy & pasting.
- Clean the code, publish. Or worse, don't publish the code!

What we should do

- Design the pipeline/architecture of the code
- Write a CLEAN and MODULAR code.
- Version monitoring by git.
- You already have a publishable version!

Guidelines

- **Clean code**: can someone else understand your code? Or even yourself in a few months/years?
    - Checklist
        - No repeated code
        - Almost every function should be less than 10 lines
        - Is your code modular? Can you change your codebase so that you can run your method on new dataset in less than an hour?

- **Backup/version monitoring:**
    - Use git

Case study: A-GEM

https://github.com/facebookresearch/agem/

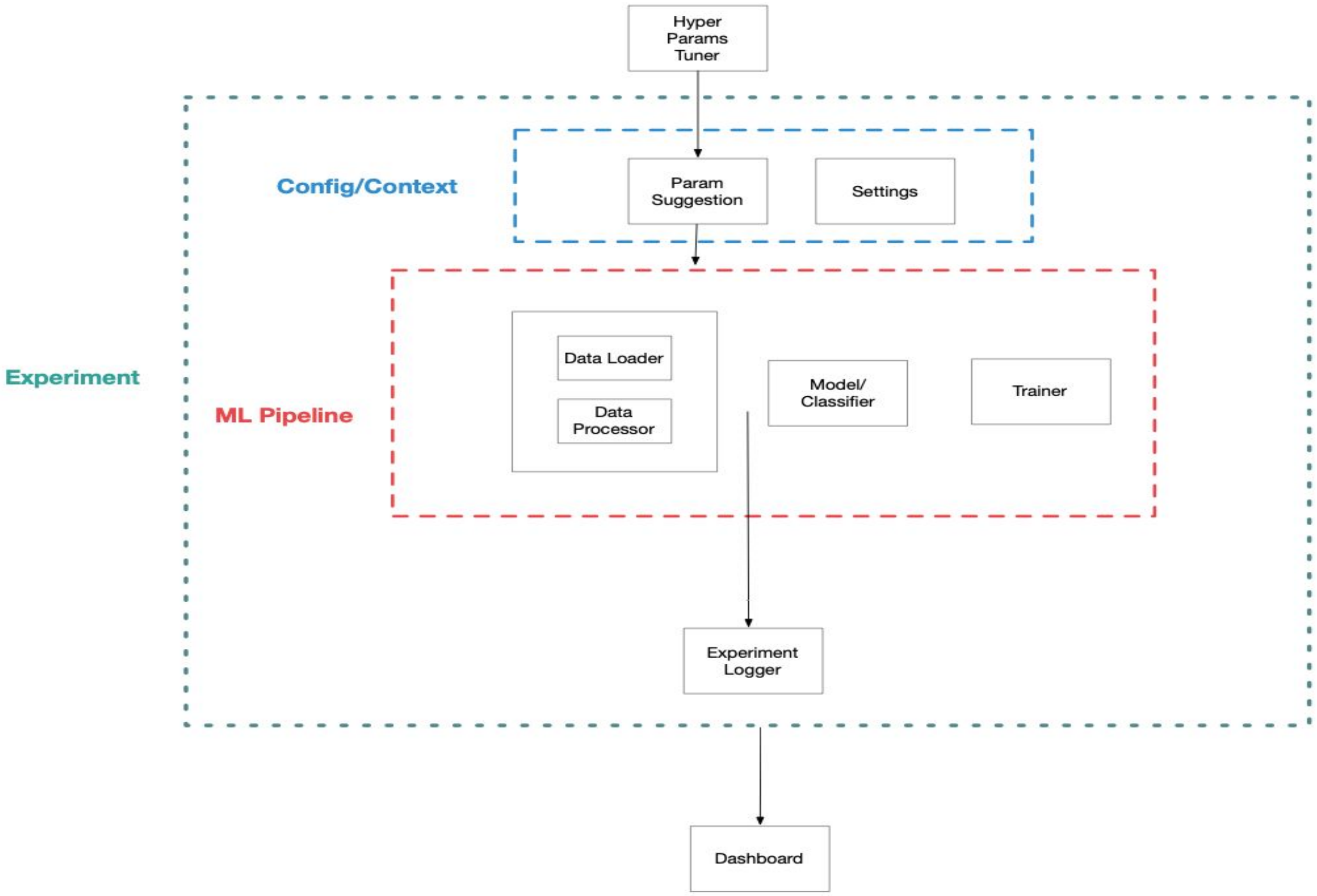
Running/Reporting Phase

What we do

- Run with few hyper-params locally.
- Log the results in a csv sheet/file and calculate the metrics.

What we should do

- Use hyper-param tuner and run with various params on a cluster/gpu machine.
- Log the results using an experiment manager

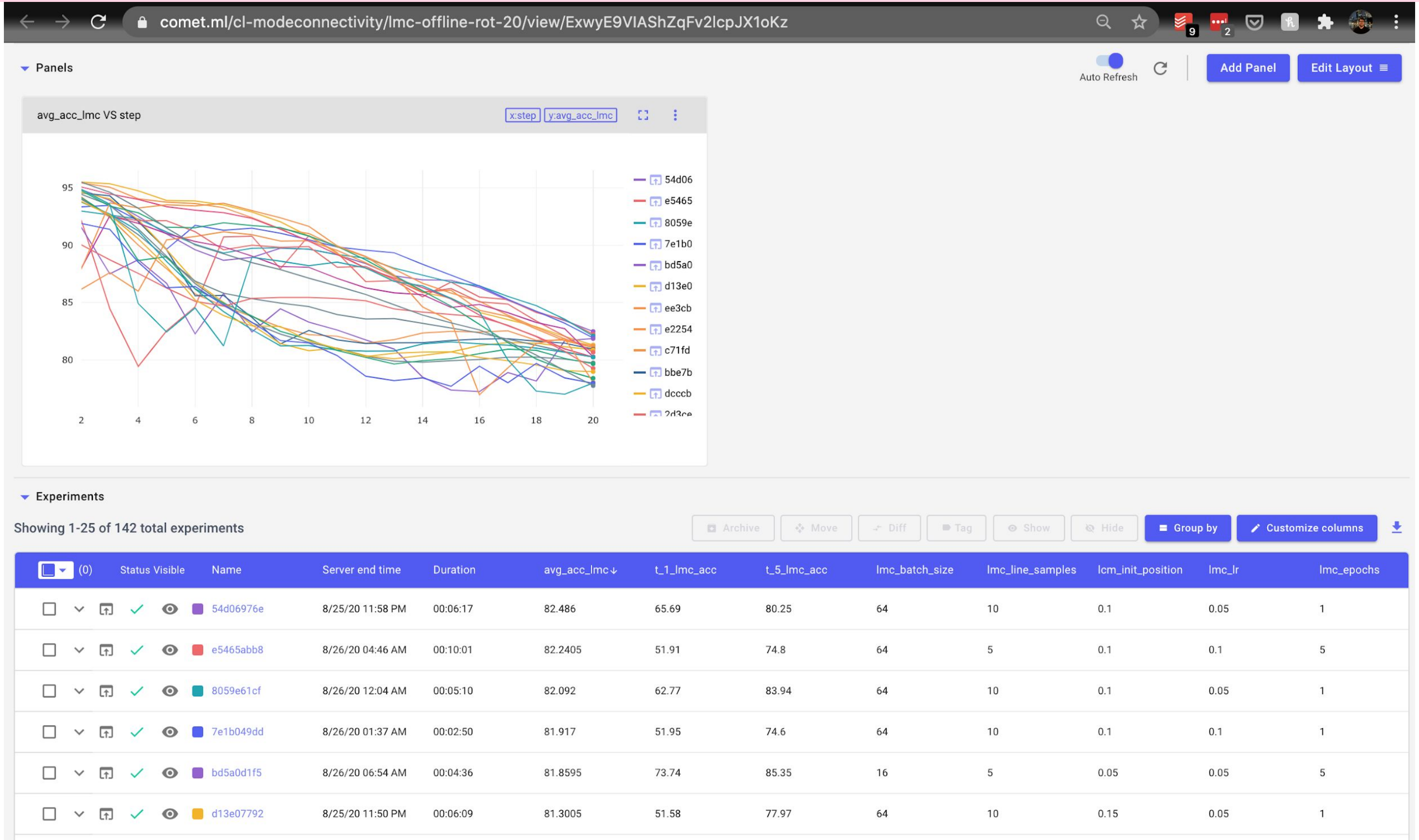


Hyper Params Tuner
Config/Context
Param Suggestion
Settings
Experiment
ML Pipeline
Data Loader
Data Processor
Model/ Classifier
Trainer
Experiment Logger
Dashboard

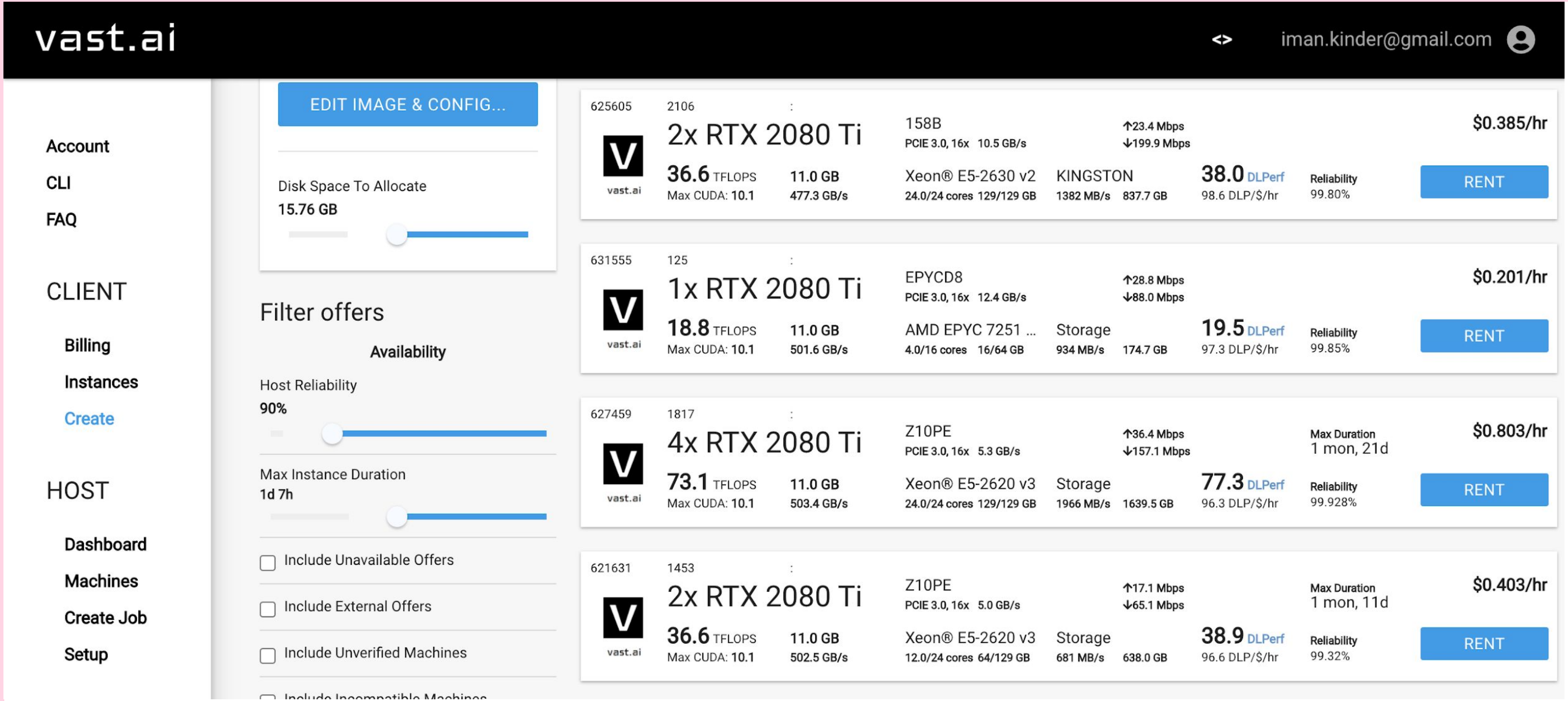
Example: Hyper-param tuning

```
{ "num_tasks": {"_type":"choice", "_value":[20]},
  "memory_size": {"_type": "choice", "_value": [200]},
  "momentum": {"_type": "choice", "_value": [0.8]},
  "dropout": {"_type": "choice", "_value": [0.0, 0.25]},
  "lr_decay": {"_type": "choice", "_value": [1.0, 0.7, 0.5]},

  "seq_lr": {"_type": "choice", "_value": [0.1, 0.05, 0.01]},
  "seq_batch_size": {"_type": "choice", "_value": [16, 32, 64]},
  "seq_epochs": {"_type": "choice", "_value": [1]},

  "lmc_lr": {"_type": "choice", "_value": [0.001, 0.005, 0.01]},
  "lmc_batch_size": {"_type": "choice", "_value": [16, 32, 64]},
  "lcm_init_position": {"_type": "choice", "_value": [0.25, 0.5, 0.75]},
  "lmc_line_samples" : {"_type": "choice", "_value": [5, 10]},
  "lmc_epochs": {"_type": "choice", "_value": [1]}
}
```

Experiment management with comet.ml



Vast.ai for GPU machines



Final Tips

Final Tips

- Every hyper-param/setting should be stored in a global object!
  - Learning rate, optimizer, batch size, dropout rate
  - Number of hidden layers, number of epochs

- Every step and every result, should be stored online!
  - Model weights/checkpoints
  - The config
  - Metrics

- Basically, you shouldn’t lose anything if someone crushes your laptop with a hammer right now!

Thank You!

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