# Catch Me If You Can: Keeping up with ML Models in Production

Shreya Shankar

June 2021

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  - Responsibilities spanning recruiting, SWE, ML, product, and more

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- Industry places emphasis on Agile working style
- In industry, we want to train few models but do *lots* of inference
- What happens beyond the validation or test set?

# The depressing truth about ML IRL

- 87% of data science projects don't make it to production[1]

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- Data in the "real world" is always changing
- Showing high performance on a fixed train and validation set $\neq$ consistent high performance when that model is deployed

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  - Demo'ing mltrace, a coarse-grained lineage & tracing tool

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  - Feature lag: our system only learns about raw data after it has been produced
  - Label lag: our system only learns of the label after the ride has occurred
- The evaluation metric will inherently be lagging
- We might not be able to train on the most recent data

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  - ETL intermediate output distributions
  - Can get tedious if you have many features or steps in ETL
- Still unclear how to quantify, detect, and act on

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  - In my experience, this method has flagged distributions as "significantly different" more than I want it to
  - In the era of "big data" (we have millions of data points), p-values are not useful to look at[2]

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# How do you know when the data has "drifted?"

**You don't really know.**

An unsatisfying solution is to retrain the model to be as fresh as possible. What kinds of bugs will surface when you are continually training models?

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- Many more

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- Very few (if any) people have end-to-end visibility on an ML pipeline
- Underdeveloped monitoring and tracing tools
- So many artifacts to keep track of, especially if you retrain your models

# Retraining regularly

Monitoring is not enough; we also need to retrain.

- Use MLFlow Model Registry[3] to keep track of which model is the best model

Now, we need some tracing[4]...

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- At inference time, pull the latest/best model from our model registry

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- Alpha release[5] contains Python API to log run information and UI to view traces for outputs

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  - When there is a bug, whose backlog do you put it on?
  - Enable people who may not have developed the model to investigate the bug

# mltrace concepts

- Pipelines are made of components (ex: cleaning, featuregen, split, train)

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[7] https://docs.dagster.io/concepts/solids-pipelines/solids
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    - User creates instance of `ComponentRun` object and calls `log_component_run` on the object

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# mltrace integration example

```python
def clean_data(raw_data_filename: str, raw_df: pd.DataFrame,
                              month: str, year: str,
                             component: str) -> str:
    first, last = calendar.monthrange(int(year), int(month))
    first_day = f'{year}-{month}-{first:02d}'
    last_day = f'{year}-{month}-{last:02d}'
    clean_df = helpers.remove_zero_fare_and_oob_rows(
        raw_df, first_day, last_day)

    # Write "clean" df to s3
    output_path = io.save_output_df(clean_df, component)

    return output_path
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                              output_vars=['output_path'])
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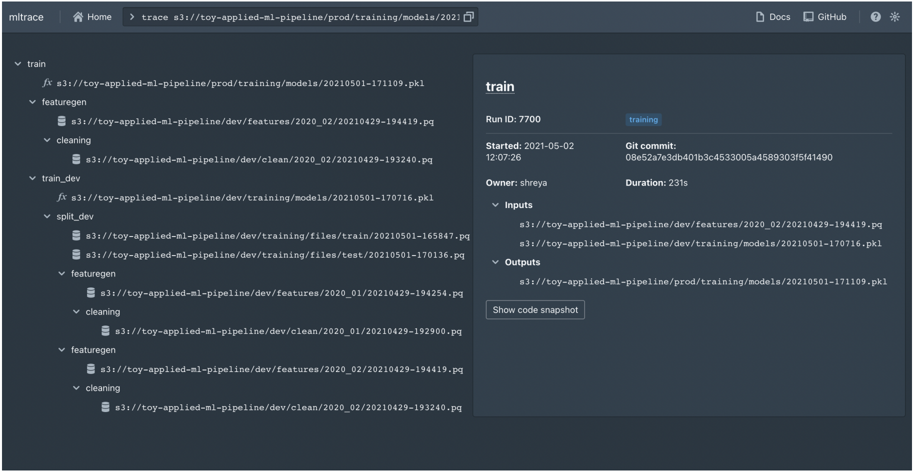
# mltrace integration example

```
from mltrace import create_component, tag_component,
                              register

create_component('cleaning', 'Cleans the raw data with basic
                               OOB criteria.', 'shreya')
tag_component('cleaning', ['etl'])

# Run function
raw_df = io.read_file(month, year)
raw_data_filename = io.get_raw_data_filename('2020', '01')
output_path = clean_data(raw_data_filename, raw_df, '01', '
                              2020', 'clean/2020_01')
print(output_path)
```

# mltrace UI demo



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- Lineage at the record/row level

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- Introduced mltrace, a tool developed for ML pipelines that performs coarse-grained lineage and tracing

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[10] D'Amour et al., *Underspecification Presents Challenges for Credibility in Modern Machine Learning*.

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- How to enable anyone to build dashboards or monitor pipelines?
  - ML people know what to monitor, infra people know how to monitor
  - We should strive to build tools to allow engineers and data scientists to be more self sufficient

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- Code for this talk:
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- Toy ML Pipeline with mltrace, Prometheus, and Grafana integrations: `https://github.com/shreyashankar/toy-ml-pipeline/tree/shreyashankar/db`

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- Toy ML Pipeline with mltrace, Prometheus, and Grafana integrations: https://github.com/shreyashankar/toy-ml-pipeline/tree/shreyashankar/db
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- Thank you!

# References

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