Data-centric ML pipeline for data drift and data preprocessing

ML enables efficient hardware verification

- The goal of hardware verification is to find almost all design bugs in time to achieve near bug-free design.
- But hardware design space is massive. Thus, engineers use constrained random testing; they generate random test inputs to probe various design spaces. Each test returns pass/failure where a failure means a bug is found.
- We use ML to increase efficiency in hardware verification by guiding the testing behavior.



Data problems cause most MLOps issues

Data preprocessing

- Need for dtype correction (e.g., "True")
- Difficult-to-understand features w/ high dimensionality
- Complex regex patterns in string features
- Multiple interpretations available for categorical features

Data drift



dtype of a feature can change over time: (e.g., bool -> str) Automation feasibility

- Frequent interventions from domain experts required to understand any changes in data
- Brittle ML pipeline due to frequent data drift
- Heavy reliance on domain experts: delayed early deployment

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Principles

- Data-driven: the ML pipeline preprocesses raw data based on the contents of the data (less dependent on domain experts)
- Flexible & robust: adaptive to changes in training data
- Automated: digests raw data automatically

Overview

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Schema for monitoring, casting, and preprocessing

	aypoo		
	Inferred	Casting	Preprocessor
Feature 0	"mixed"	dtype(' <u')< td=""><td>"lists"</td></u')<>	"lists"
Feature 1	"mixed-integer-U"	dtype(' <u')< td=""><td>"nominal_str"</td></u')<>	"nominal_str"

- Generated every time new data arrives (training and serving)
- Infer granular dtypes using pandas.api.types.infer_dtype and numpy.dtype.kind

Pre-defined mapping for translating the inferred dtypes to others From schema to preprocessor

- Backbone: a scikit-learn pipeline with a ColumnTransformer step
- Pre-defined preprocessing methods (e.g., OneHotEncoder for "nominal_str") for all dtypes fetched to build column transformer
- Easy to observe and change data preprocessing methods Data-drift handling
- Not all data drifts are significant
- Schema built during serving and compared with training schema
- First, mismatches are resolved (using dummies) and serving job is run. Any mismatches are logged and trigger alerts. Vs. Pandera

Pandera: data validation

- Data validation checks
- Hypothesis testing
- Data synthesis
- Custom row-based transformation
- Type inference (nur
- Type casting
- Detect column mis
- Error logging

Data-centric ML pipeline

Observable: data preprocessing is transparent and trackable

dtypes

	Data preprocessing
mpy)	 More granular type inference
smatch	 Build preprocessor from schema Resolve column mismatch

- hyperparameters





Remaining challenges

Compute and pipeline structure

- transformed datasets
- without any data leakage

Interplay between data and model

- others?
- hyperparameters?

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Difficult to tune data preprocessing methods without any

redundant computation unless transformed data is pre-

computed and saved (numerous combos are possible)

Difficult to configure a streamlined ML pipeline with multiple

Even more challenging to build a pipeline with cross validation

Generally challenging to solve interoperability issues when using multiple libraries in a highly customized setting

Why some features prefer specific preprocessing methods over

What is the role of data preprocessing when tuning model