Robust, End-to-end Online Machine Learning Applications with Flyte, Pandera and, Streamlit



Niels Bantilan, Union.ai



- 📜 B.A. Biology and Dance
- \blacksquare M.P.H., Sociomedical Science and Public Health Informatics
- La Machine Learning Engineer @ Union.ai
- 🋪 Flytekit Maintainer
- Author and Maintainer of Pandera
- Make DS/ML practitioners more productive





- 🤖 Offline vs. Online Learning
- Use Case: Weather Forecasting
- Pandera, and Streamlit
- Pipeline Architecture
- Demo
- 🎁 Takeaways



Motivation

"Full-stack Data Scientist / ML engineer"

What even is that

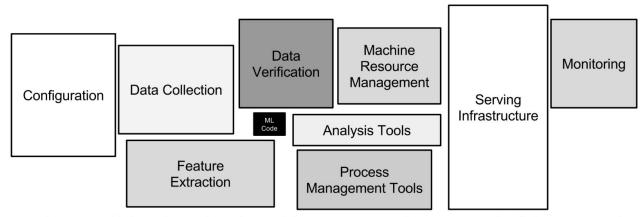
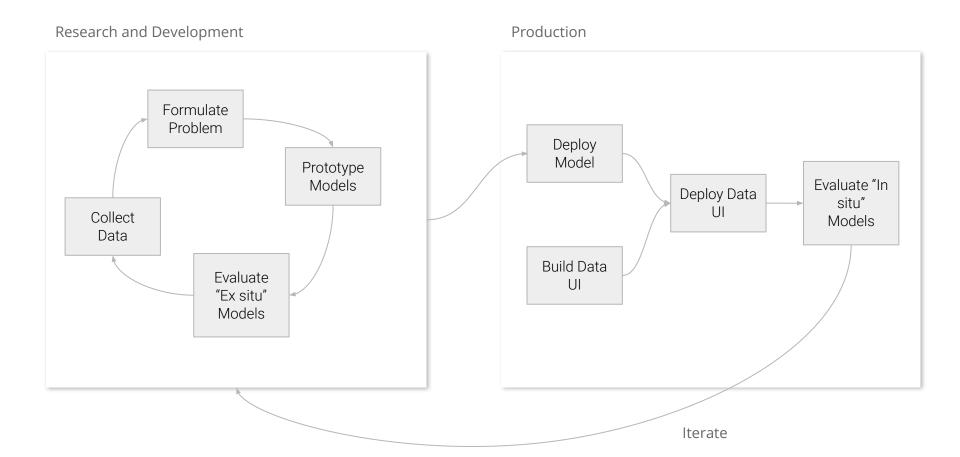


Figure 1: Only a small fraction of real-world ML systems is composed of the ML code, as shown by the small black box in the middle. The required surrounding infrastructure is vast and complex.





How far can a small data team get building and shipping production model-driven data products?

Challenge

Build an online learning system that updates a model hourly and displays forecasts on a web UI

Why?

It forces the practitioner to think about:

- How to manage incremental data acquisition
- Model updates in production as a first class citizen
- Evaluation metrics where model sees each example only once



Offline vs. Online Learning

A crash course



Offline Learning

Learning a model on a static training dataset, potentially with multiple passes through the dataset.

Online Learning

Learning a model with training instances that present themselves to the model only once, in some temporal fashion.

Why Online Learning?

- Your data isn't static, e.g. data is generated as a function of time
- Your data might be too large to practically store/train a model on all at once
- You can't assume I.I.D. data, e.g. today's
 \$\biglie\$ depends on yesterday's
- Your model needs to be as up-to-date as possible due to the dynamic nature of the data

Use Case: Weather Forecasting

Hourly temperature forecasts



Products Services Resources News About Contact



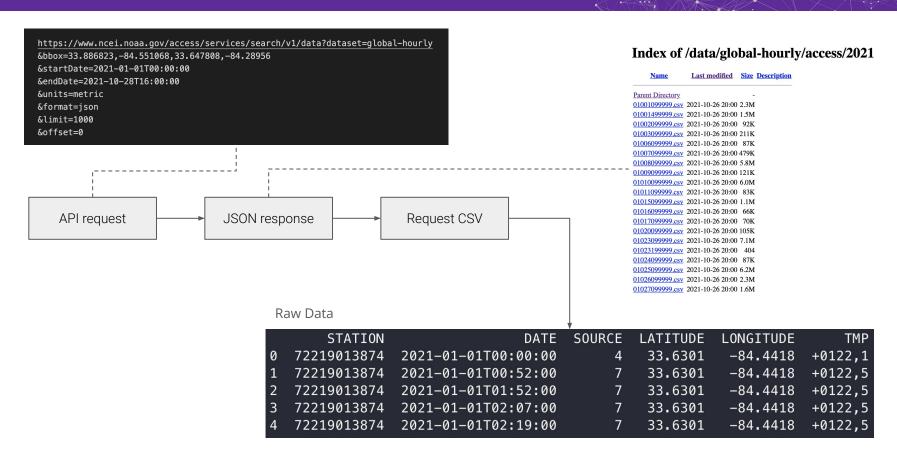
Home | Products | Land-Based Station | Global Hourly - Integrated Surface Database (ISD)

Global Hourly - Integrated Surface Database (ISD)

The Integrated Surface Database (ISD) is a global database that consists of hourly and synoptic surface observations compiled from numerous sources into a single common ASCII format and common data model. ISD integrates data from more than 100 original data sources, including numerous data formats that were key-entered from paper forms during the 1950s–1970s time frame. ISD includes numerous parameters such as wind speed and direction, wind gust, temperature, dew point, cloud data, sea level pressure, altimeter setting, station pressure, present weather, visibility, precipitation amounts for various time periods, snow depth, and various other elements as observed by each station.



Use Case: Weather Forecasting





Autoregressive Model

$$X_t = c + \sum_{i=1}^p arphi_i X_{t-i} + arepsilon_t$$

Actual Implementation: Include one-hot encoded time-based features, e.g. day of week, day of month, month of year, etc.



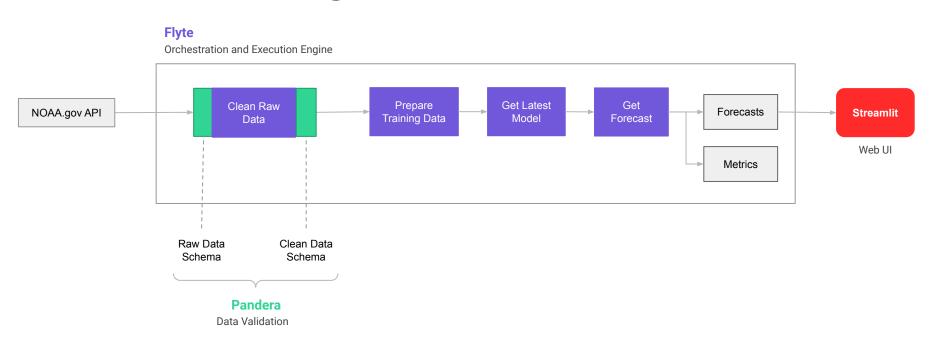
Evaluation Metric

Exponentially-weighted Mean of the Absolute Error

```
eps = 0.1
ewmae = 0
for X, y in training_data:
   y_pred = model(X)
   ewmae = eps * abs(y - y_pred) + (1 - eps) * ewmae
```



High-level Overview



Quickstart: Flyte

A brief introduction



Flyte is Like the Stratosphere

Kubernetes-first Workflow Orchestration Engine

Automated Data Lineage Tracking Platform



Type-safe Data Pipeline Language

Write Tasks: Isolated Pieces of Data Processing

```
from flytekit import task
@task
def transform data(df: pd.DataFrame) -> pd.DataFrame:
   df["c"] = df["a"] + df["b"]
   df["d"] = df["c"] * 2
   return df
@task
def aggregate_data(df: pd.DataFrame) -> pd.DataFrame:
   return df.mean().to_frame().transpose()
```

Compose Workflows: Connect Tasks Together

```
from flytekit import workflow

@workflow
def pipeline(df: pd.DataFrame) -> pd.DataFrame:
    transformed_df = transform_data(df=df)
    return aggregate_data(df=transformed_df)
```



Caching Made Easy

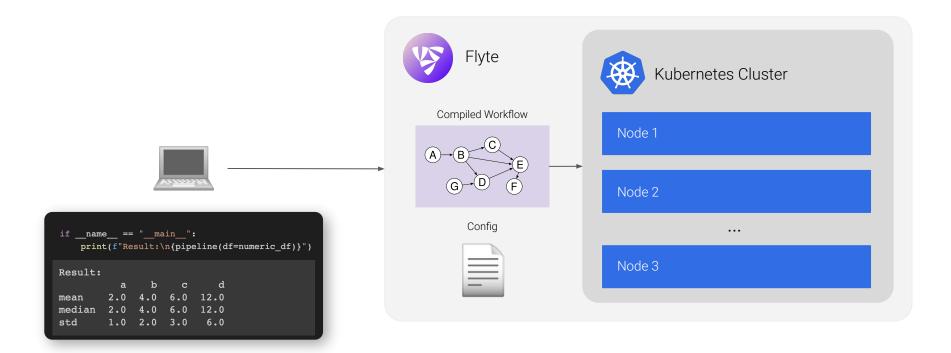
```
from datetime import datetime
@task(cache=True, cache_version="1.0")
def get data(from: datetime, to: datetime) -> pd.DataFrame:
   df = pd.read_sql(...). # some expensive query
   return df
```

Ask for Resources, and you Shall Receive

```
from flytekit import Resources
from flytekit.types.file import FlyteFile
from flytekit.types.directory import FlyteDirectory

@task(
    request_resources=Resources(gpu="2", mem="500Mi", storage="1Gi")
    limit_resources=Resources(gpu="2", mem="750Mi", storage="2Gi")
)
def train_model(training_data: FlyteDirectory) -> FlyteFile:
    ...
```

Develop Locally, Deploy to Scale





Integrate with Existing Ecosystem of Tools



























Quickstart: Pandera

A brief introduction













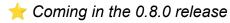












Encode assumptions about dataframes as schemas

import pandera as pa from pandera.typing import Series, Index class TransformInput(pa.SchemaModel): a: Series[int] b: Series[int] schema inheritance class TransformOutput(TransformInput): c: Series[int] d: Series[int] class AggregateOutput(pa.SchemaModel): regex columns: Series[float] = pa.Field(alias="a|b|c|d", regex=True) column-matching index: Index[str] = pa.Field(isin=["mean", "median", "std"])

Index support

Extend pandera's built-in validation checks

Custom checks are just class methods

```
class TransformInput(pa.SchemaModel):
    a: Series[int] = pa.Field(ge=0)
    b: Series[int] = pa.Field(ge=0)

    @pa.check("a")

    def check_even(cls, series: Series) -> Series[bool]:
        """Check for even numbers"""
        return series % 2 == 0
```

Custom checks

Easily integrate with your pipeline via function decorators

Use pandera SchemaModels in python type annotations

Validate dataframe types at runtime

```
from pandera.typing import DataFrame
@pa.check types
def transform data(df: DataFrame[TransformInput]) -> DataFrame[TransformOutput]:
    df["c"] = df["a"] + df["b"]
    df["d"] = df["c"] * 2
    return df
@pa.check types
def aggregate data(df: DataFrame[TransformOutput]) -> DataFrame[AggregateOutput]:
    return df.agg(["mean", "median", "std"])
```

Easily integrates with Flytekit

```
pip install flytekitplugins-pandera
```

```
@task
def transform data(df: DataFrame[TransformInput]) -> DataFrame[TransformOutput]:
    df["c"] = df["a"] + df["b"]
    df["d"] = df["c"] * 2
   return df
```

Get informative errors if something goes wrong

Column not present in dataframe

```
try:
   transform data(pd.DataFrame({"b": [4, 5, 6]}))
except pa.errors.SchemaError as e:
   print(e)
error in check types decorator of function 'transform data': column 'a' not in dataframe
   b
```

Get informative errors if something goes wrong

Column has unexpected data type

```
@pa.check types
def transform data(df: DataFrame[TransformInput]) -> DataFrame[TransformOutput]:
   df["c"] = df["a"] + df["b"]
   df["d"] = df["c"] * 2
    return df
    transform data(pd.DataFrame({"a": ["x", "y", "z"], "b": [4, 5, 6]}))
except pa.errors.SchemaError as e:
   print(e)
error in check types decorator of function 'transform data': expected series 'a' to have type int64, got object
```

Get informative errors if something goes wrong

Assumptions violated: presence of negative numbers and odd numbers



Inspect failure cases

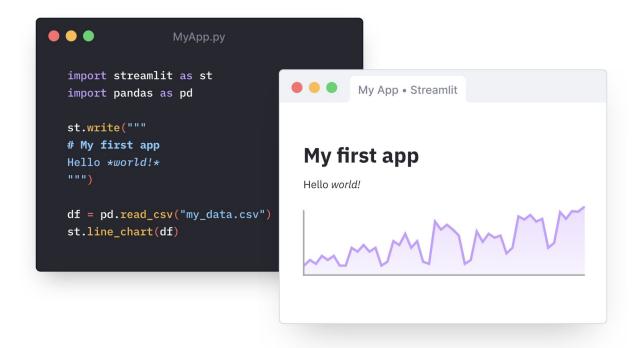
Quickstart: Streamlit

A brief introduction





Make Interactive UIs via Scripting





Streamlit >> Flyte

```
import pandas as pd
import streamlit as st
from flytekit.remote import FlyteRemote
remote = FlyteRemote()
st.title("My Flyte App")
def get_flyte_output():
    [latest_execution, *_], _ = remote.client.list_executions_paginated(...)
   execution_output: pd.DataFrame = remote.client.get_execution_data(latest_execution.id)
   return execution_output
st.linechart(get_flyte_output())
```

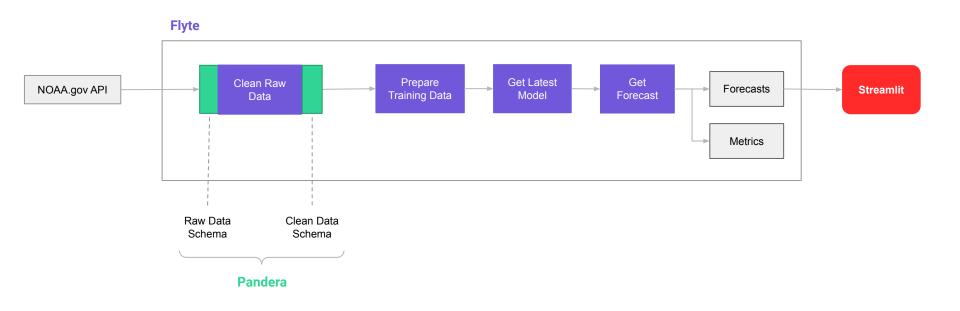
Pipeline Architecture

Putting all the Pieces Together





High-level Overview



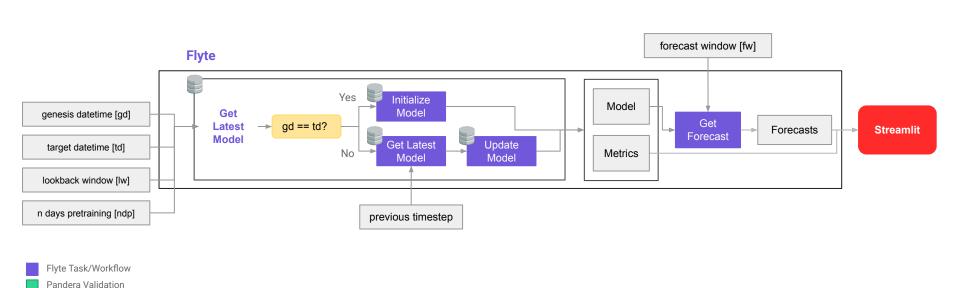
Requirements

- Support incremental model updates and pre-training
- Don't waste requests fetching data from the NOAA API
- Implement online evaluation metrics



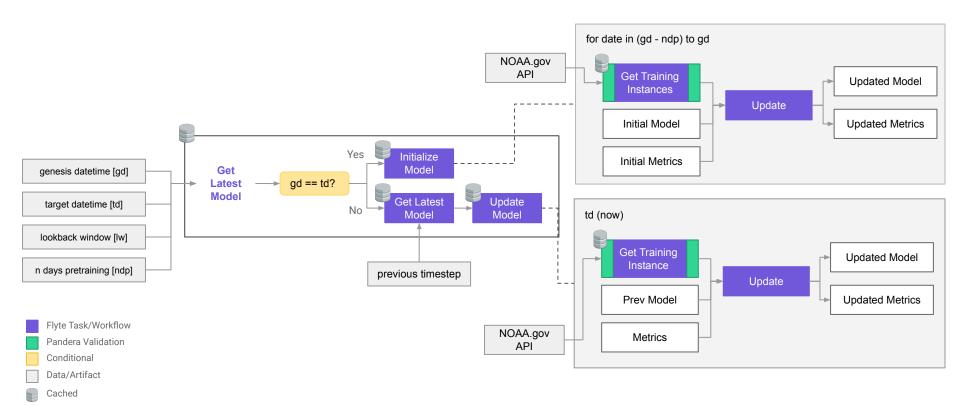
Conditional Data/Artifact Cached

Support Incremental Model Updates and Pretraining





Don't Waste Requests Fetching Data from NOAA API





Online Model Evaluation

Exponentially-weighted Mean of the Absolute Error

```
train ewmae = 0
valid_ewmae = 0
eps = 0.1
for X, y in training_data:
    y_pred = model(X)
 \rightarrow valid ewmae = eps * abs(y - y pred) + (1 - eps) * valid ewmae
   model.fit_partial(X, y)
    y_pred = model(X)
-▶ train ewmae = eps * abs(y - y pred) + (1 - eps) * train ewmae
```

Demo

Web UI and Flyte Console https://bit.ly/flyte-weather-forecasting



Takeaways

Towards "Full-stack Data Science and ML engineering" teams



Flyte

Flyte provides a powerful platform for type-safe, scalable, and reproducible model-driven applications



Pandera

Pandera enables type safety for dataframe-like objects through an expressive, lightweight API



Streamlit

Streamlit simplifies and accelerates web UI development for anyone who can script





Contact

twitter: @cosmicBboy github: cosmicBboy

linkedin: https://www.linkedin.com/in/nbantilan

Links

Weather Forecasting app: https://bit.ly/flyte-weather-forecasting Weather Forecasting repo: https://github.com/flyteorg/flytelab

Flyte repo: https://github.com/flyteorg/flyte

Pandera repo: https://github.com/pandera-dev/pandera
Streamlit repo: https://github.com/streamlit/streamlit

