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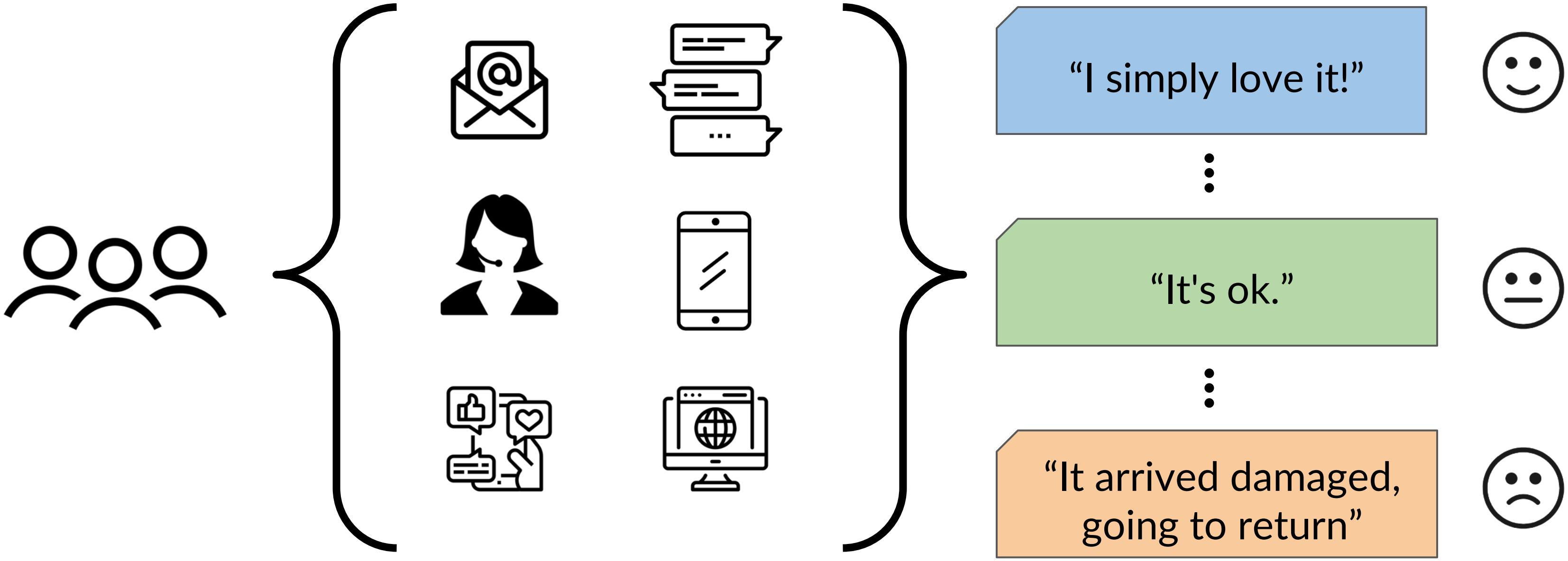
DeepLearning.AI

aws

Practical Data Science

Use AutoML to Train a Text Classifier

Multi-class classification for sentiment analysis of product reviews



Machine Learning Workflow

Ingest & Analyze	Prepare & Transform	Train & Tune	Deploy & Manage
Data exploration	Feature engineering	Automated ML	Model deployment
Bias detection	Feature store	Model train and tune	Automated pipelines
Amazon S3 & Amazon Athena	Amazon SageMaker Data Wrangler	Amazon SageMaker Autopilot	Amazon SageMaker Endpoints
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Amazon SageMaker Data Wrangler & Clarify	Amazon SageMaker Feature Store	Amazon SageMaker Hyperparameter Tuning	Amazon SageMaker Pipelines

Automated Machine Learning

(AutoML)

Model Building Challenges

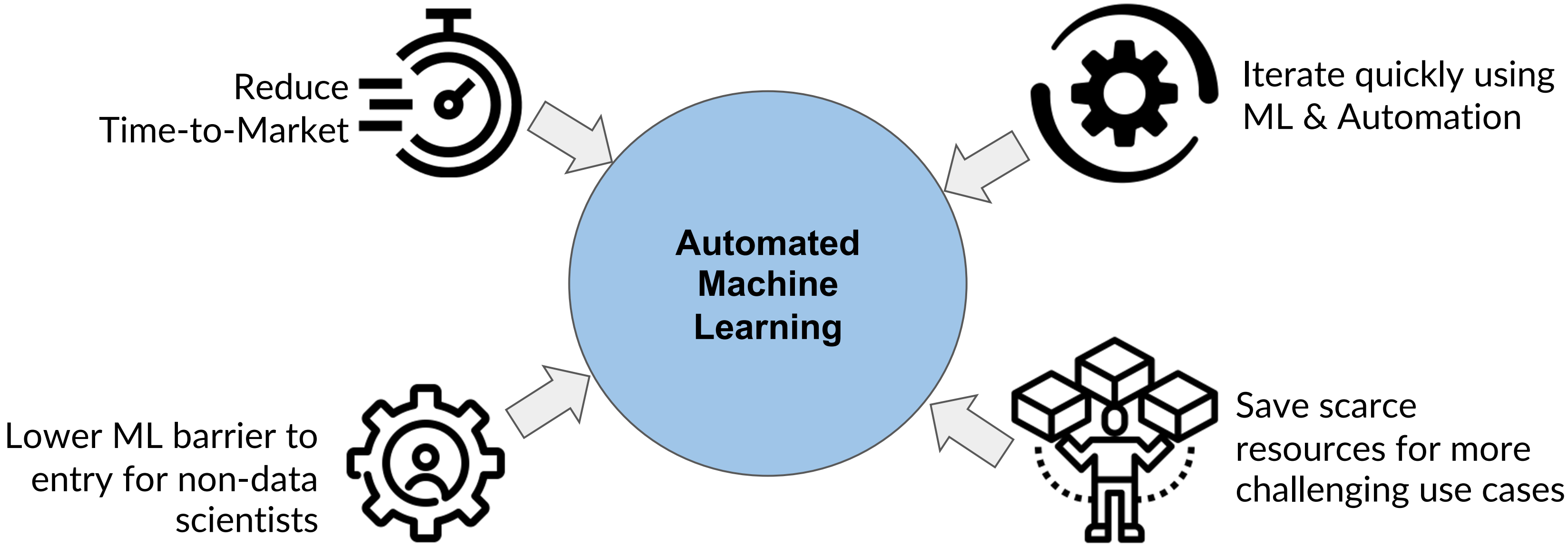
Ability to reduce Time-to-Market

Ability to iterate quickly

Lack of ML skillsets

Ability to optimize scarce resources & skillsets

Automated Machine Learning



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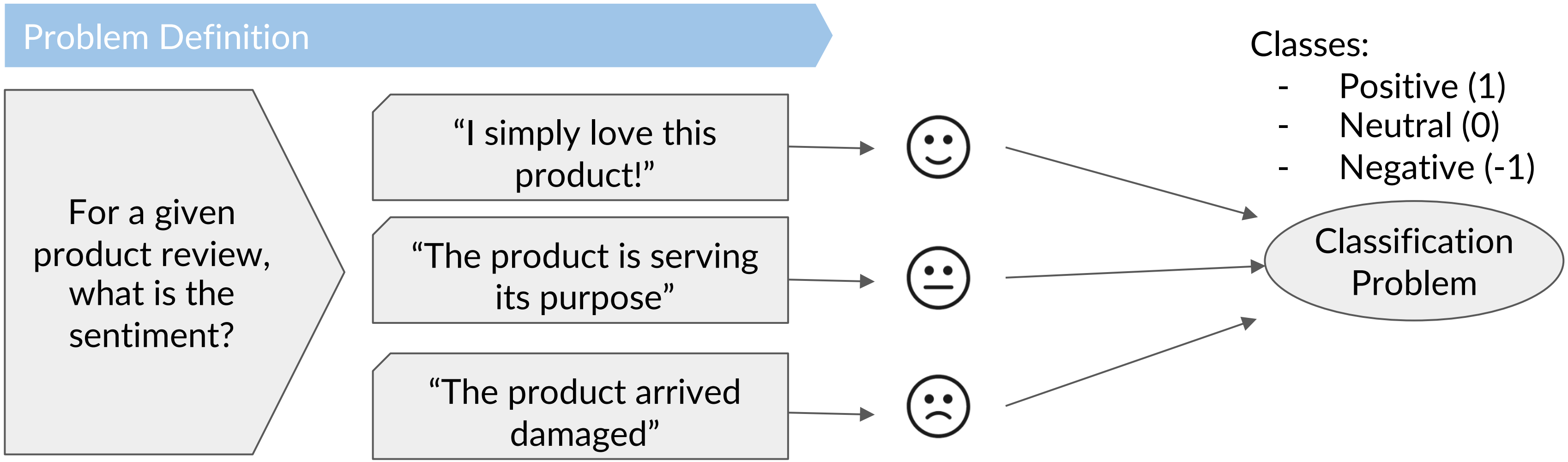
Data Preparation

Ingest & Analyze → **Prepare & Transform** → **Train & Tune** → **Deploy & Manage**

Data Analysis:

Collecting statistics, such as missing entries, quantiles, skewness, correlation with the target.



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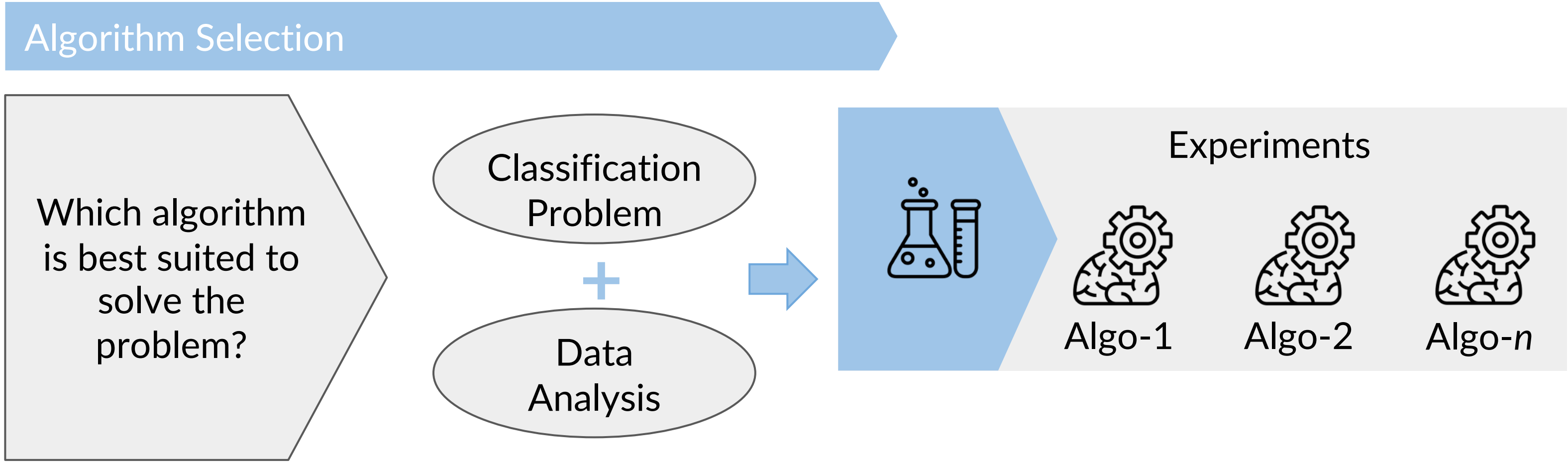


Data Preparation

Ingest & Analyze → **Prepare & Transform** → **Train & Tune** → **Deploy & Manage**

Data Analysis:

Collecting statistics, such as missing values, quantiles, skewness, correlation with the target.

Dataset Schema Detection

review_id (Numeric)	review_text (Categorical)	sentiment (Numeric)
001	"I simply love this product!"	1
002	"The product is serving its purpose"	0
003	"The Product arrived damaged"	-1

Data Preparation

Ingest & Analyze → **Prepare & Transform** → Train & Tune → Deploy & Manage

Data Transformation:

How should data be transformed so that the model can predict as accurately as possible?

review_id	review_text	sentiment
001	“I simply love this product!”	1
002	“The product is serving its purpose”	0
003	“The Product arrived damaged”	-1

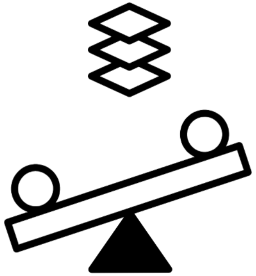
Too Many Unique Values
= Treat as Text

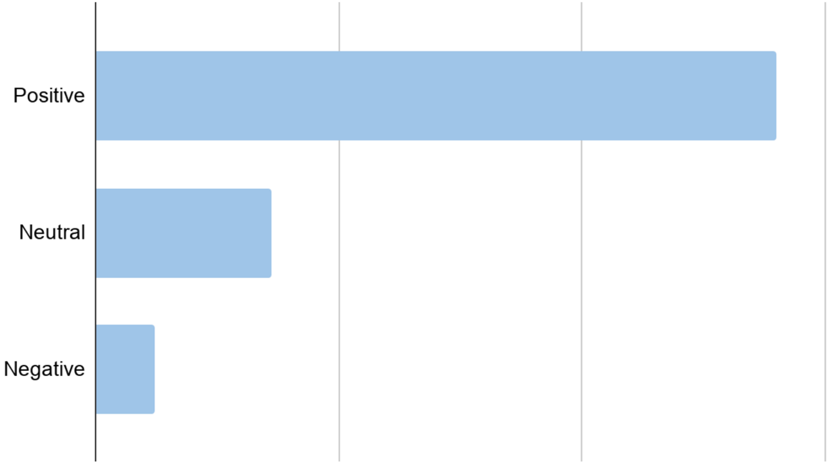
Data Preparation

Ingest & Analyze → **Prepare & Transform** → Train & Tune → Deploy & Manage

Class Imbalance:

How to identify and handle potential class imbalance?



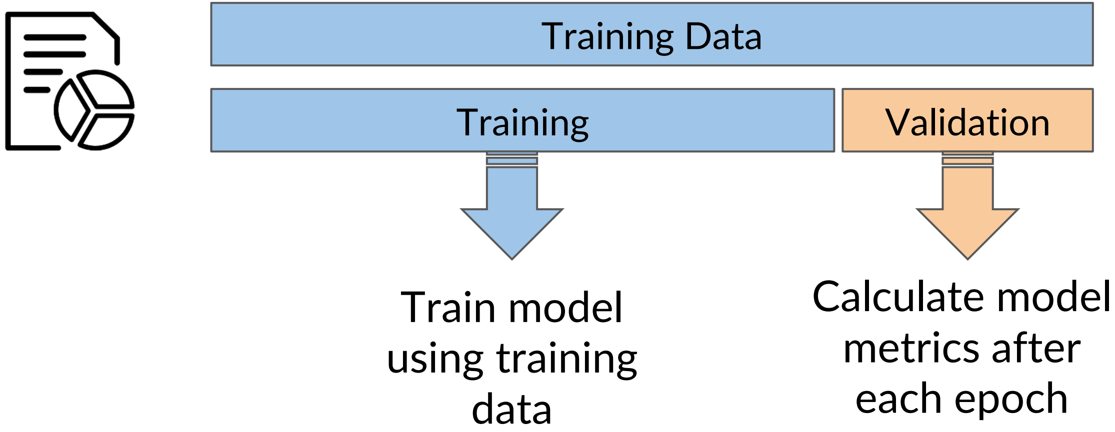


Data Preparation: Train and Validation Data Splits

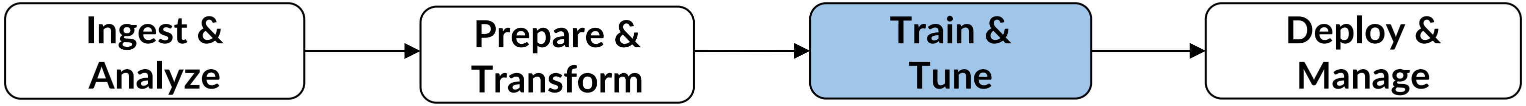
Ingest & Analyze → **Prepare & Transform** → Train & Tune → Deploy & Manage

Train-Validation Splits:

Splitting prepared data for model training, model performance, and final model evaluation

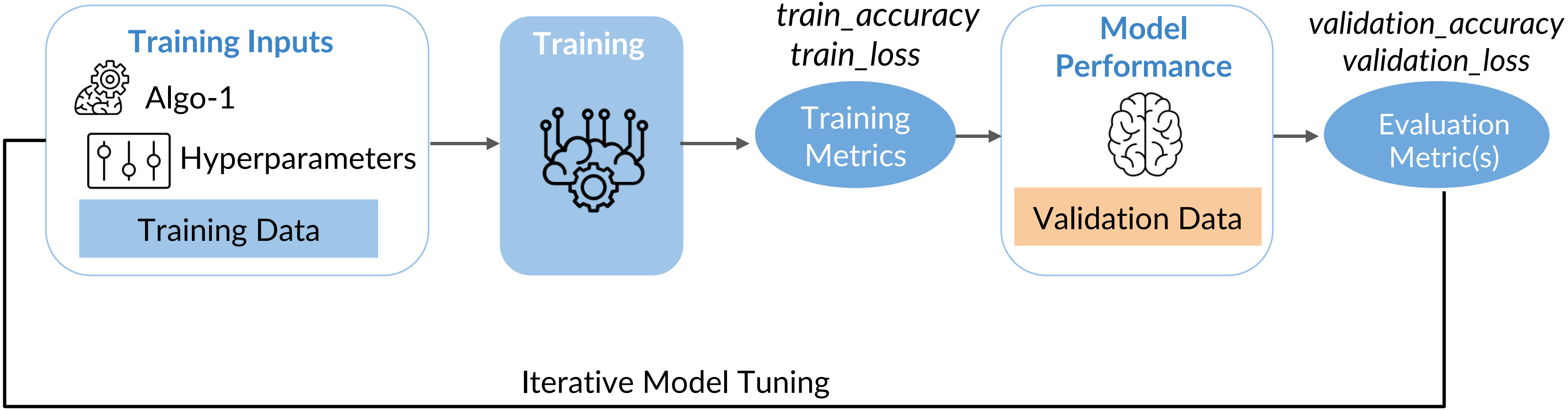


Model Training & Tuning



Model Training:

Fit the model to your data



AutoML

Ingest & Analyze → Prepare & Transform → Train & Tune → Deploy & Manage

AutoML aims at automating the process of building a model

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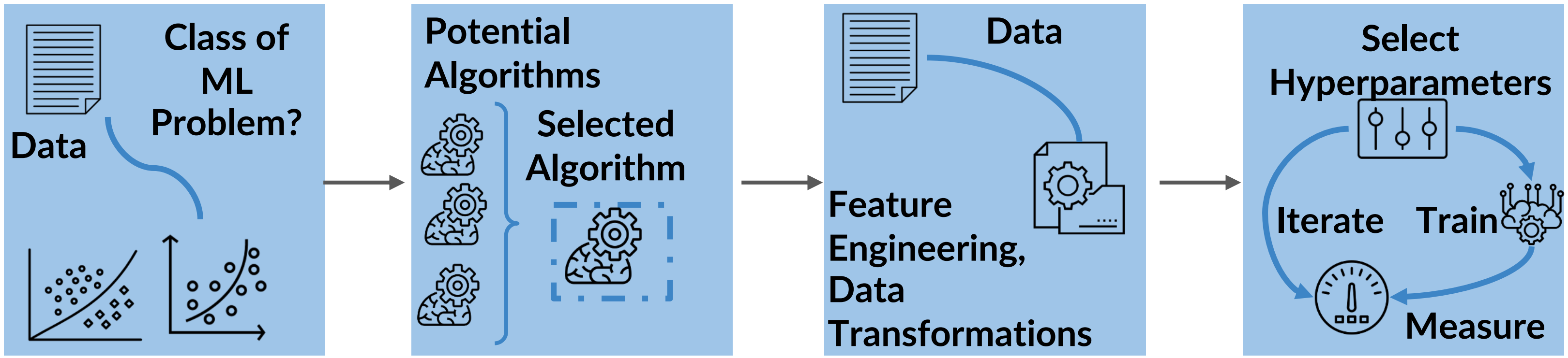

Problem Identification

Algorithm Selection

Data Preprocessing

Hyperparameter Tuning

Scenarios for AutoML

Build models without any ML expertise

- Empower more people in your organization: software developers, business people
- Let experts focus on **hard problems**

Experiment and build models at scale

- Thousands of data sets can be modeled without human intervention
- Let experts focus on **new problems**

Automate the majority of the work, then tweak

- Data cleaning, feature engineering, feature selection, etc.
- Let experts focus on high value tasks such as **domain knowledge**, and **error analysis**.

Transparency and Control are Important

Get the **best model** only

- Hard to understand it
- Hard to reproduce it manually

Get the **best model**, **all candidates**, **full source code**

- Understand how the model was built
- Keep tweaking for extra performance

AutoML

with
Amazon SageMaker Autopilot

Introduction

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AutoML with Amazon SageMaker Autopilot

Amazon SageMaker Autopilot covers all steps:

Ingest & Analyze → Prepare & Transform → Train & Tune → Deploy & Manage

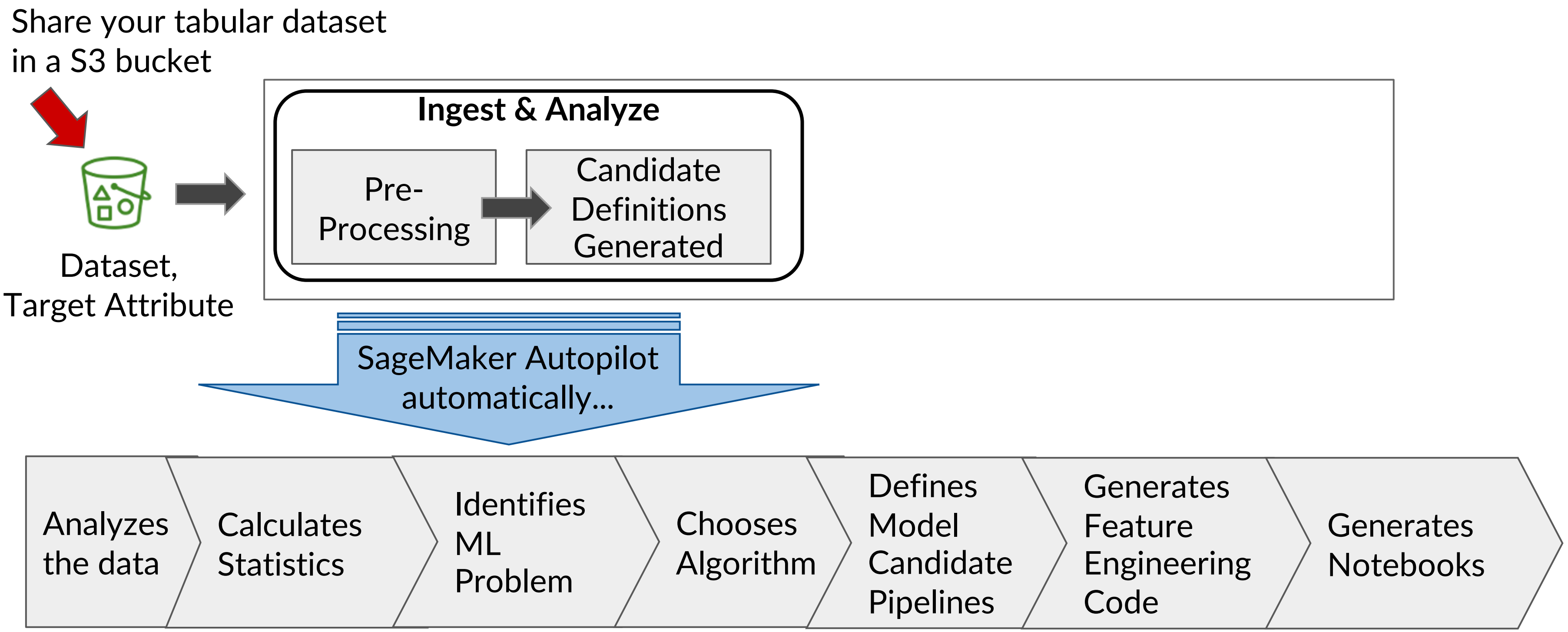
SageMaker Autopilot is fully transparent

Automatically Generated

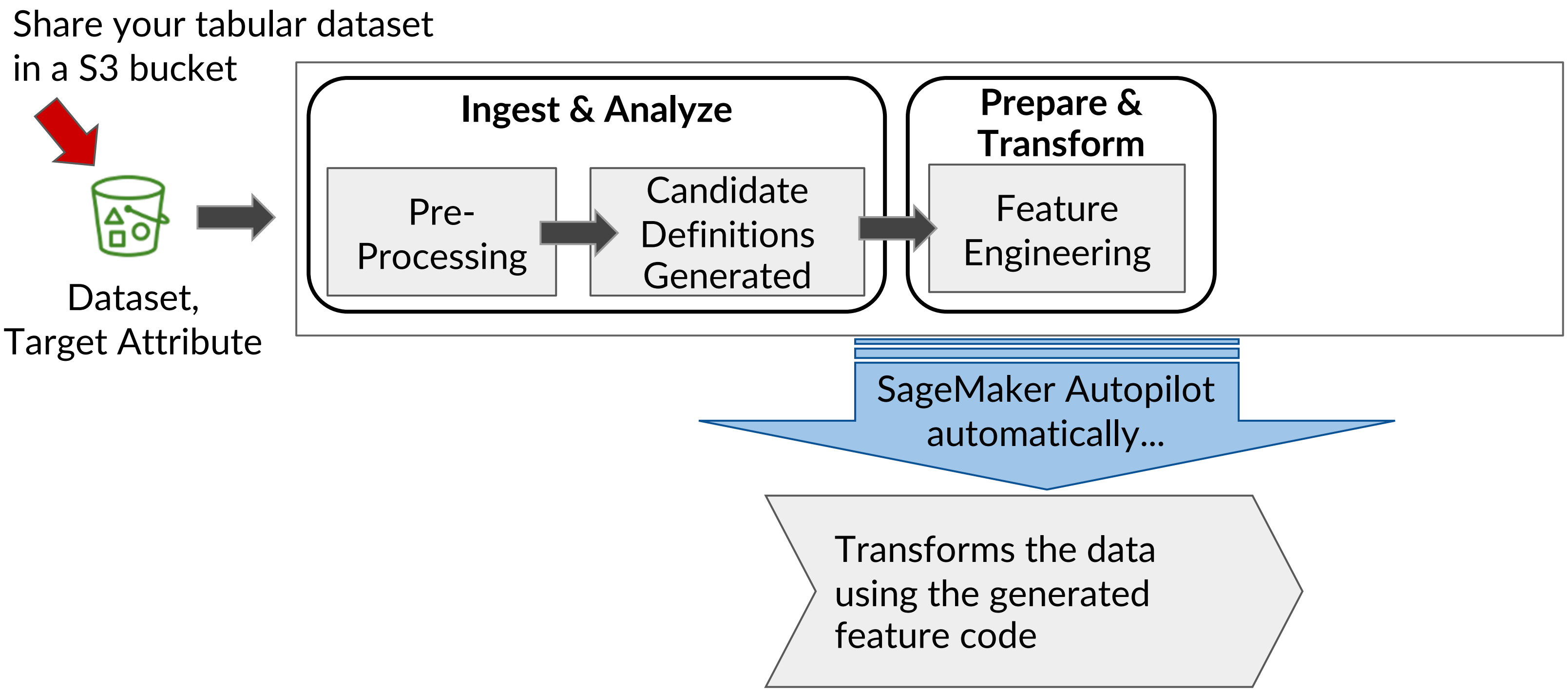
Notebooks

Code

Amazon SageMaker Autopilot at a High-Level



Amazon SageMaker Autopilot at a High-Level



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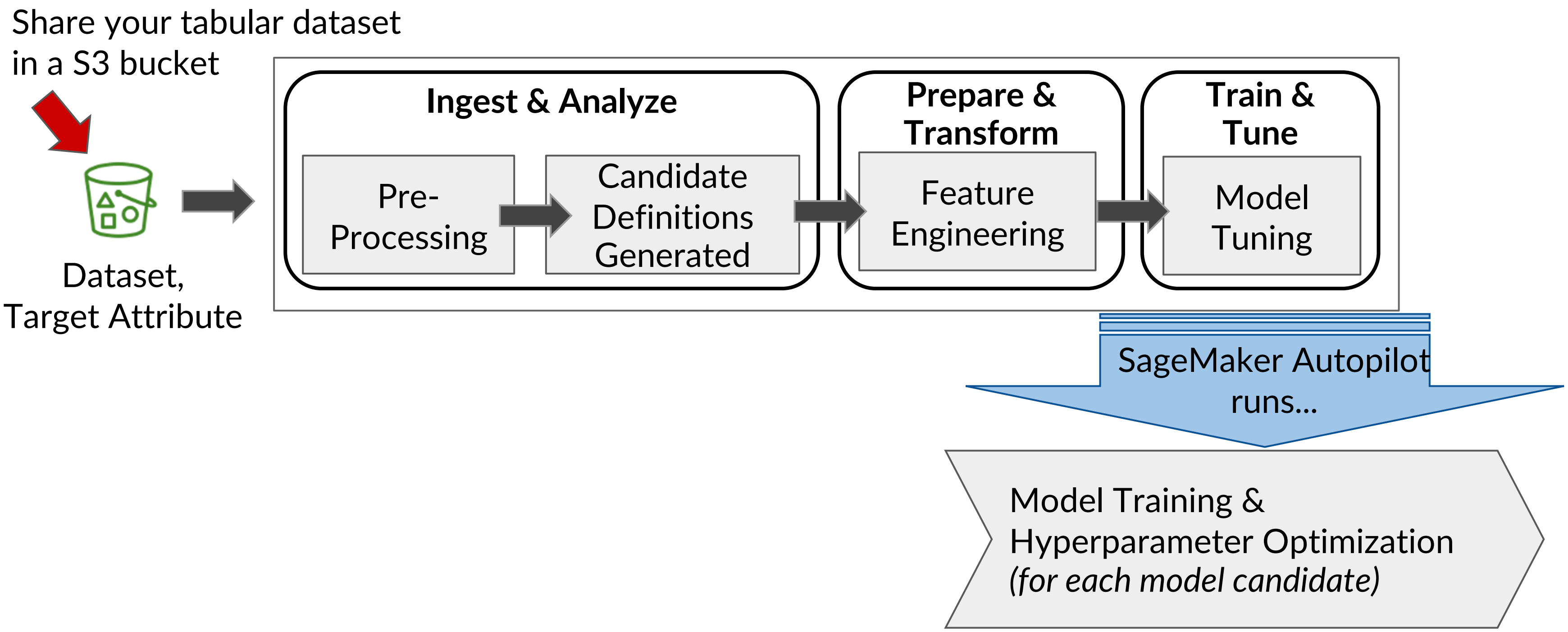
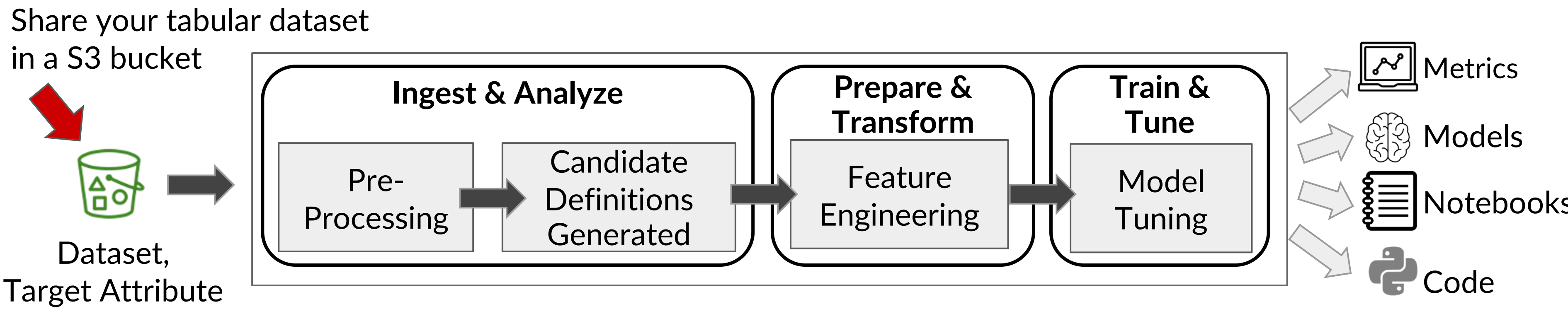


Amazon SageMaker Autopilot at a High-Level



SageMaker Autopilot shares...

- All metrics
- Leaderboard of model candidates
- Notebooks
- Code

AutoML

with
Amazon SageMaker Autopilot

Running Experiments

Amazon SageMaker Autopilot Notebook Overview

Use Case: Analyze Customer Sentiment

Goal: Use SageMaker Autopilot to find the optimal feature transformations, algorithm, and hyperparameters to produce a best performing model allowing us to predict our label (sentiment) based on product reviews (review_body)

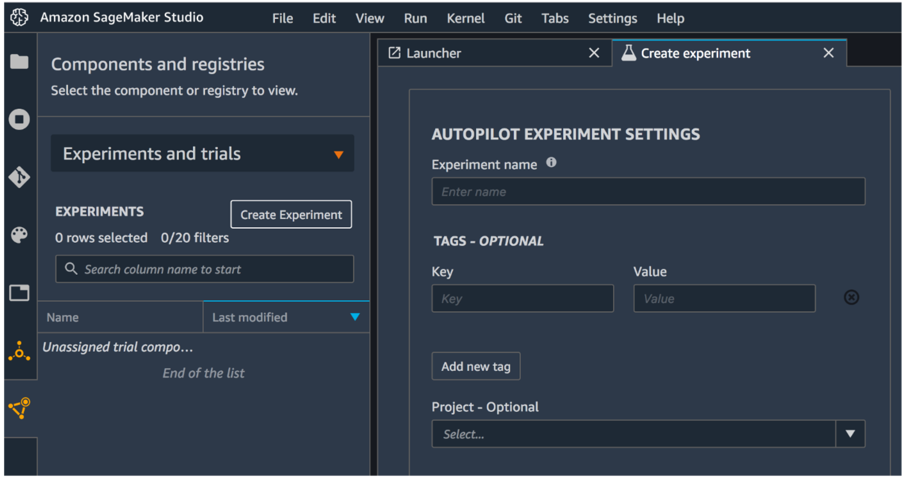
sentiment	review_body
-1	This is bad.
0	This is OK.
1	This is great!

Interacting with Amazon SageMaker Autopilot

Programmatically:

1. AWS CLI
2. AWS SDK
3. Amazon SageMaker Python SDK

~OR~



Amazon SageMaker Studio

Launch the Amazon SageMaker Autopilot Job

```
automl = sagemaker.automl.automl.AutoML(
    target_attribute_name=...
    output_path=..,
    max_candidates=3,
    role=role,
    max_runtime_per_training_job_in_seconds=1200,
    total_job_runtime_in_seconds=7200 # max automl job runtime in seconds
)

automl.fit(
    inputs=...,
)
```

Attribute to predict

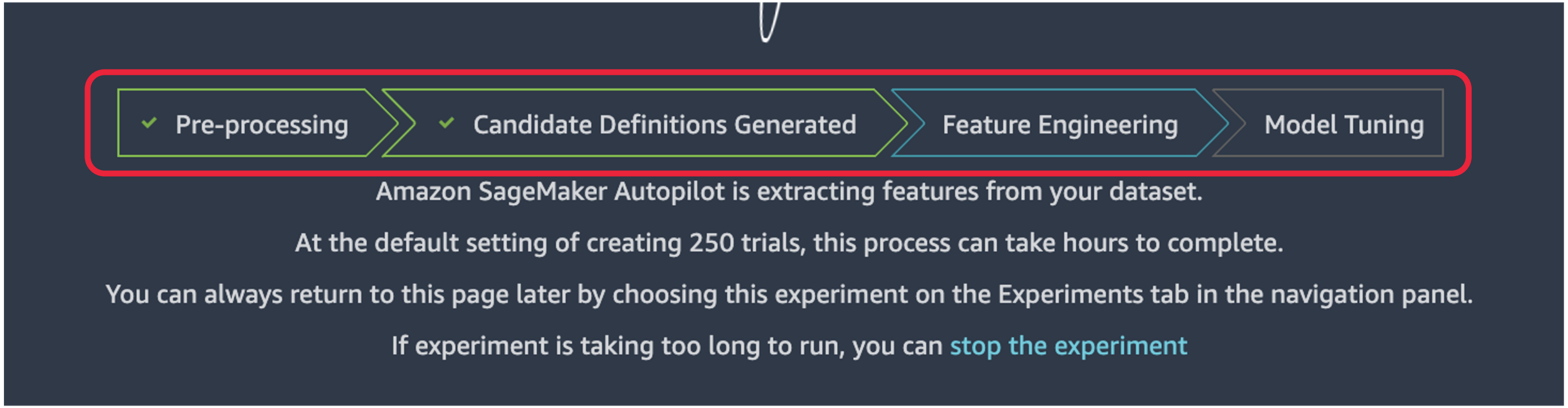
Job completion criteria

Max. training job run time

Max. AutoML job runtime

Specify input data

Monitor Progress in Amazon SageMaker Studio



API → *DescribeAutoMLJob*

Generated Code for Feature Engineering

- SageMaker Autopilot automatically performs data exploration and prepares the data for the problem type

Example(s):

Transform text features using MultiColumnTfidfVectorizer

"The Product arrived damaged"

"This product is awesome"

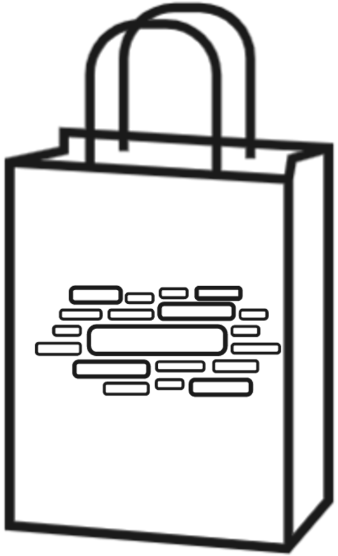
"Broke the first day"

0	.9	0	.6	0	0	0	0	0

- SageMaker Autopilot will automatically tune MultiColumnTfidfVectorizer parameters

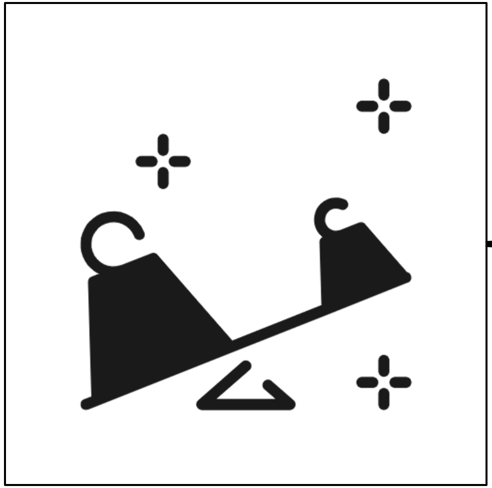
Bag-of-Words: Text as Vectors

I love this movie! It's sweet, but with satirical humor. The dialogue is great and the adventure scenes are fun... It manages to be whimsical and romantic while laughing at the conventions of the fairy tale genre. I would recommend it to just about anyone. I've seen it several times, and I'm always happy to see it again whenever I have a friend who hasn't seen it yet!



Term	**Term Count**
it	6
I	5
the	4
to	3
and	3
seen	2
yet	1
...	...

Text Mining: Measuring Word Importance



Statistical measure of word importance in corpus

↑ proportionally to the number of times a word appears in document

↓ by the frequency of the word in the corpus

tf-idf: term frequency-inverse document frequency

Computing Term Frequency (TF)

t	term
d	document
D	corpus

$$\mathrm{tf}(t,d) = \frac{\boxed{f_{t,d}}}{\boxed{\sum_{t' \in d} f_{t',d}}}$$

Computing Inverse Document Frequency (IDF)

t	term
d	document
D	corpus

$$\mathrm{idf}(t, D) = \log\left(\frac{\boxed{|D|}}{\boxed{|\{d \in D : t \in d\}|}}\right)$$

Putting It All Together: TF-IDF

$$\text{tf-idf}(t, d, D) = \text{tf}(t, d) \cdot \text{idf}(t, D)$$

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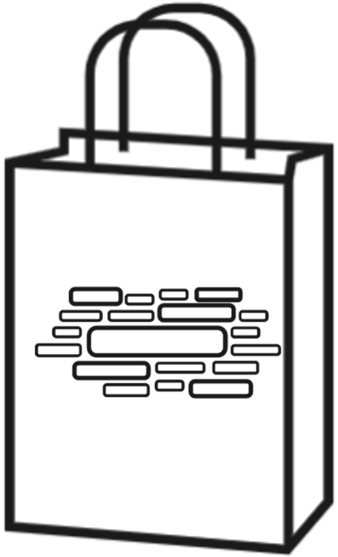


Term	TF / IDF
it	0.06
I	0.05
the	0.01
to	0.03
and	0.03
seen	0.04
yet	0.01
...	...

AutoML

with
Amazon SageMaker Autopilot

Evaluating Output

SageMaker Autopilot Generates Resources & Artifacts

Code

- Data Transformation Code
- Job Configuration Code

Notebooks

- Data Exploration
- Candidate Generation

Transformed Data

Train

Validation

Processed data used for training

Models

Candidate Models

Metrics

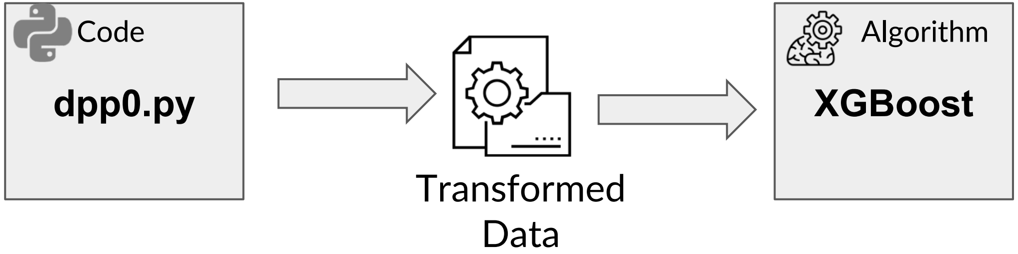
Job #	Objective Metric
tuning-job-1	0.618
tuning-job-2	0.613
tuning-job-3	0.446

Resources & Artifacts All Accessible in Amazon S3

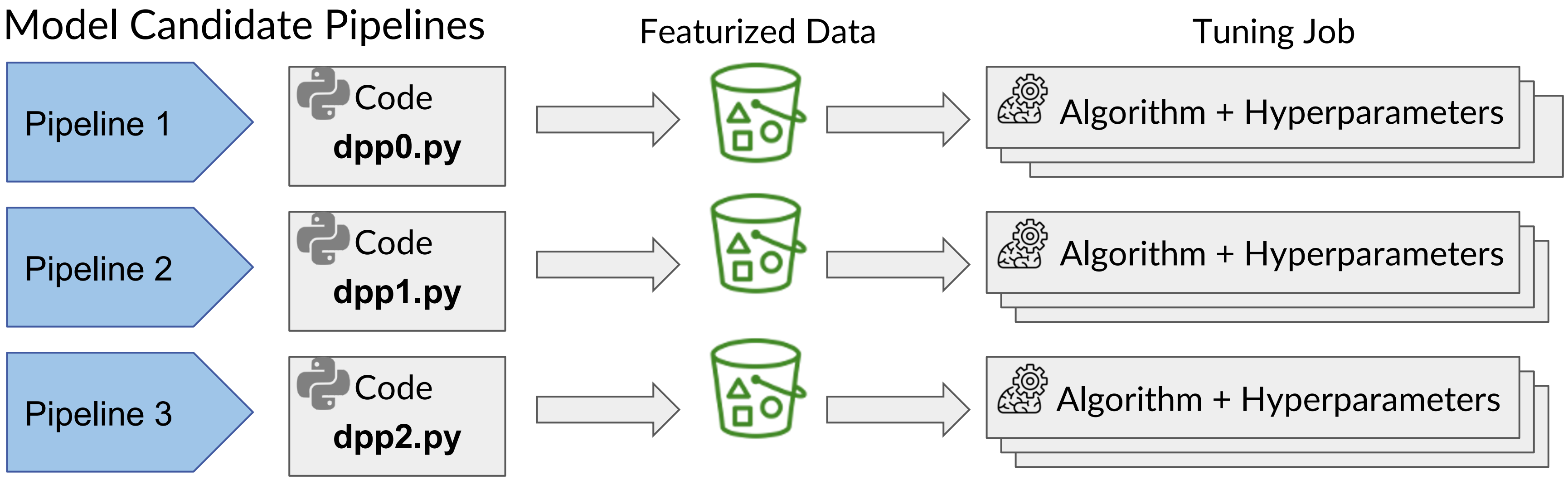
Model Candidate Pipelines

A model candidate pipeline is composed of

- the feature engineering code (i.e. dpp0.py)
- and an algorithm (i.e. XGBoost).



Executing Model Candidate Pipelines




```
automl_interactive_runner.fit_data_transformers(parallel_jobs=7)
```

Screen recording (Shelbee to insert)

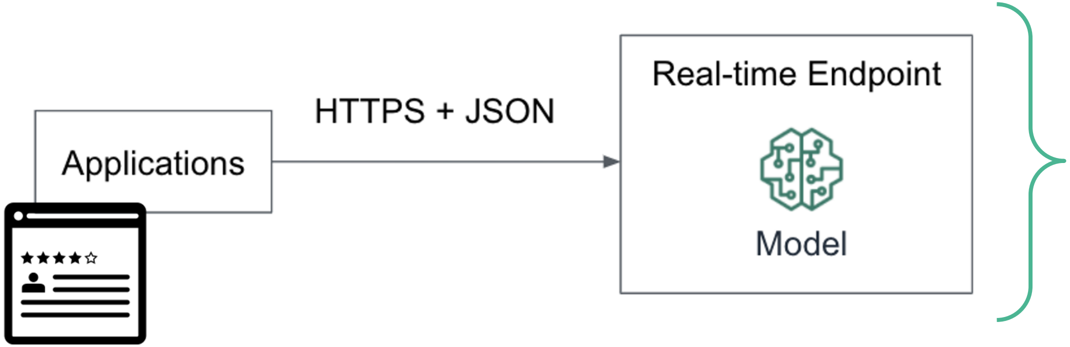
Model Hosting

Introduction

Host a Model Endpoint

Deploy the model to serve predictions in real-time.

- Optimized for **low latency** of model predictions
- Example: As product reviews are coming in through various online channels, you want to predict the sentiment



You choose:
- Instance Type/Size
- Number of Instances
- Autoscaling Options

Deploy Inference Pipeline

```
pipeline_model.deploy(initial_instance_count=1,
                      instance_type='ml.m5.2xlarge',
                      endpoint_name=pipeline_model.name,
                      wait=True)
```

Congratulations! Now you could visit the sagemaker endpoint console page to find the deployed endpoint (it'll take a few minutes to be in service).

The `PipelineModel` has multiple containers of the following:

- **Data Transformation Container:** a container built from the model we selected and trained during the data transformer sections
- **Algorithm Container:** a container built from the trained model we selected above from the best HPO training job.
- **Inverse Label Transformer Container:** a container that converts numerical intermediate prediction value back to non-numerical label value.

Inference Pipeline