Per Entity Training Pipelines in Apache Beam

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ML6

BEAM SUMMIT
NYC 2023

About ML6

We are a group of AI and machine learning experts building custom AI solutions.

Amongst our engineers we have several Apache Beam contributors.

Agenda

- Development of ML applications
  - What is training?
  - What is MLOps?
- What does per entity training mean?
  - Training multiple models rather than a single model?
  - Why use a per entity strategy
- Example per entity training pipeline
- Bonus: Using trained models in a RunInference pipeline

What is machine learning model training?

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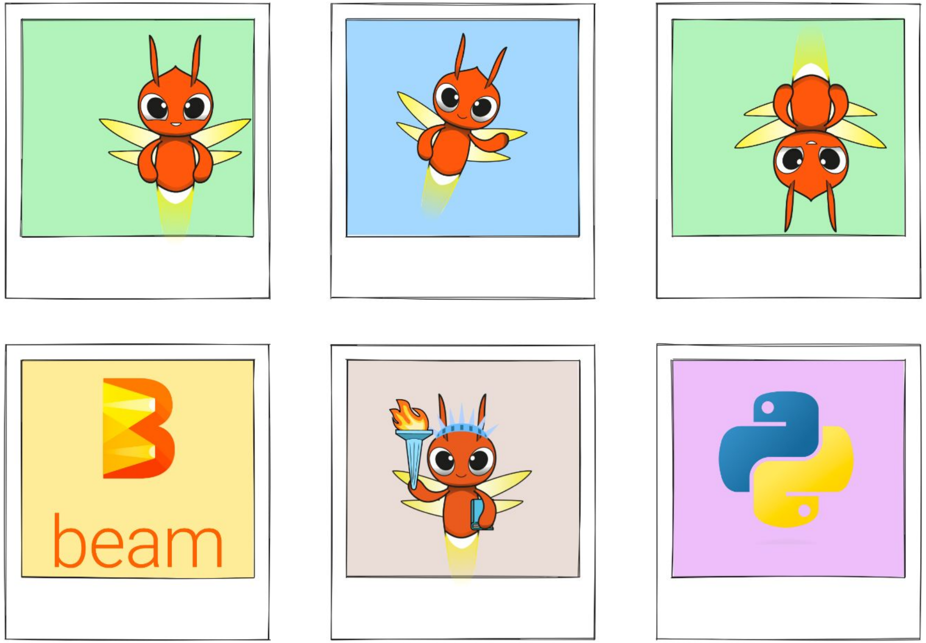
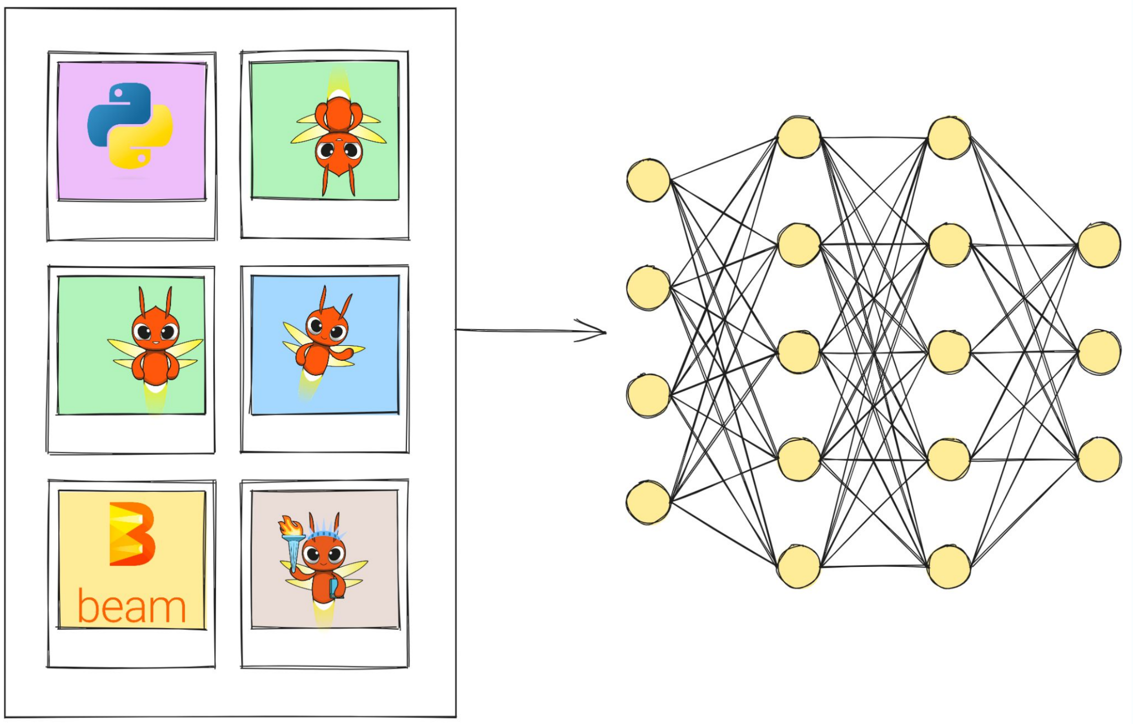
```
def contains_firefly():
    ...
```



Writing logic to detect the Beam macot is almost impossible

What is training a machine learning model?



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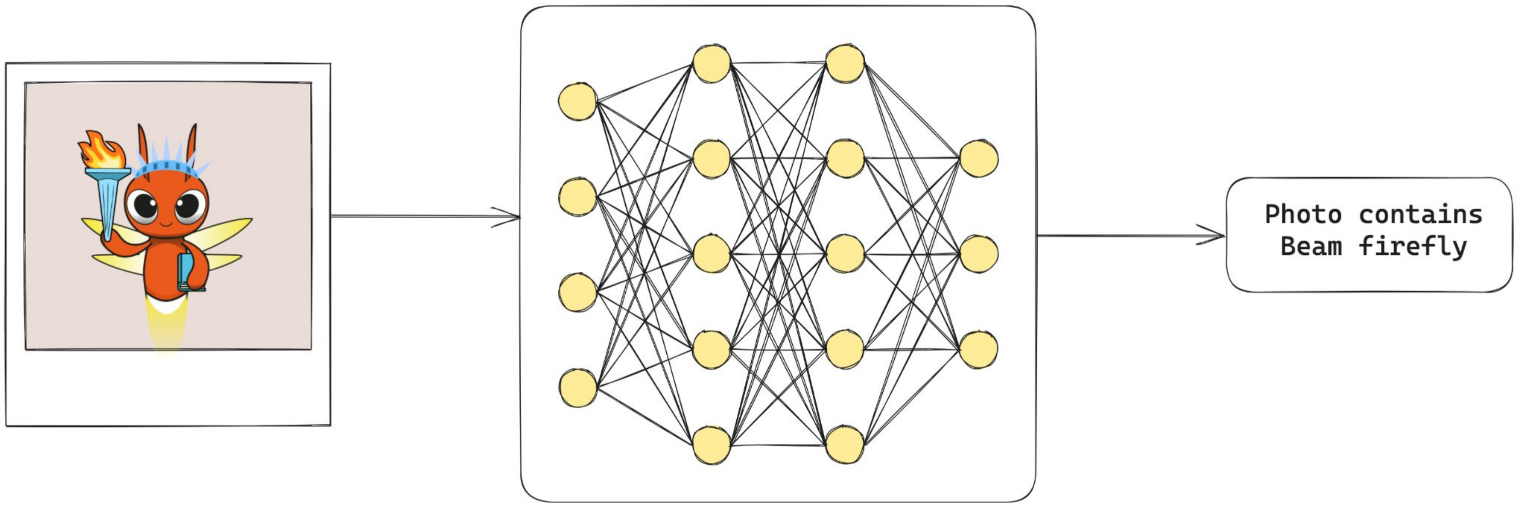
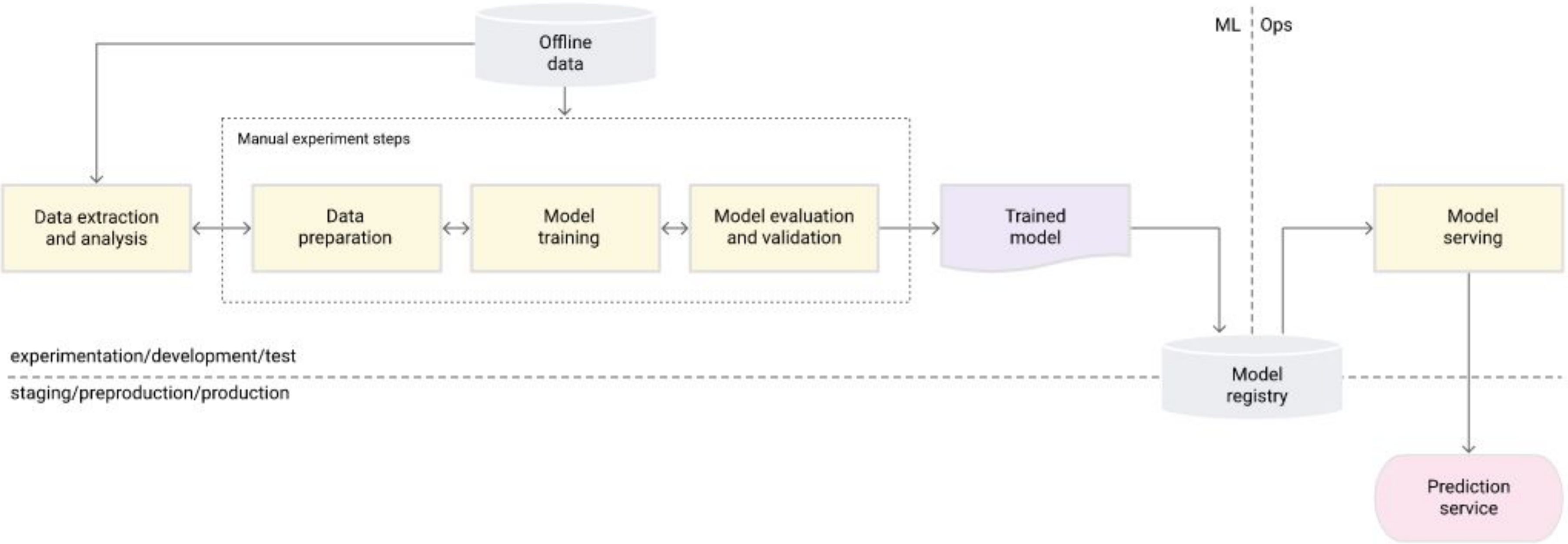
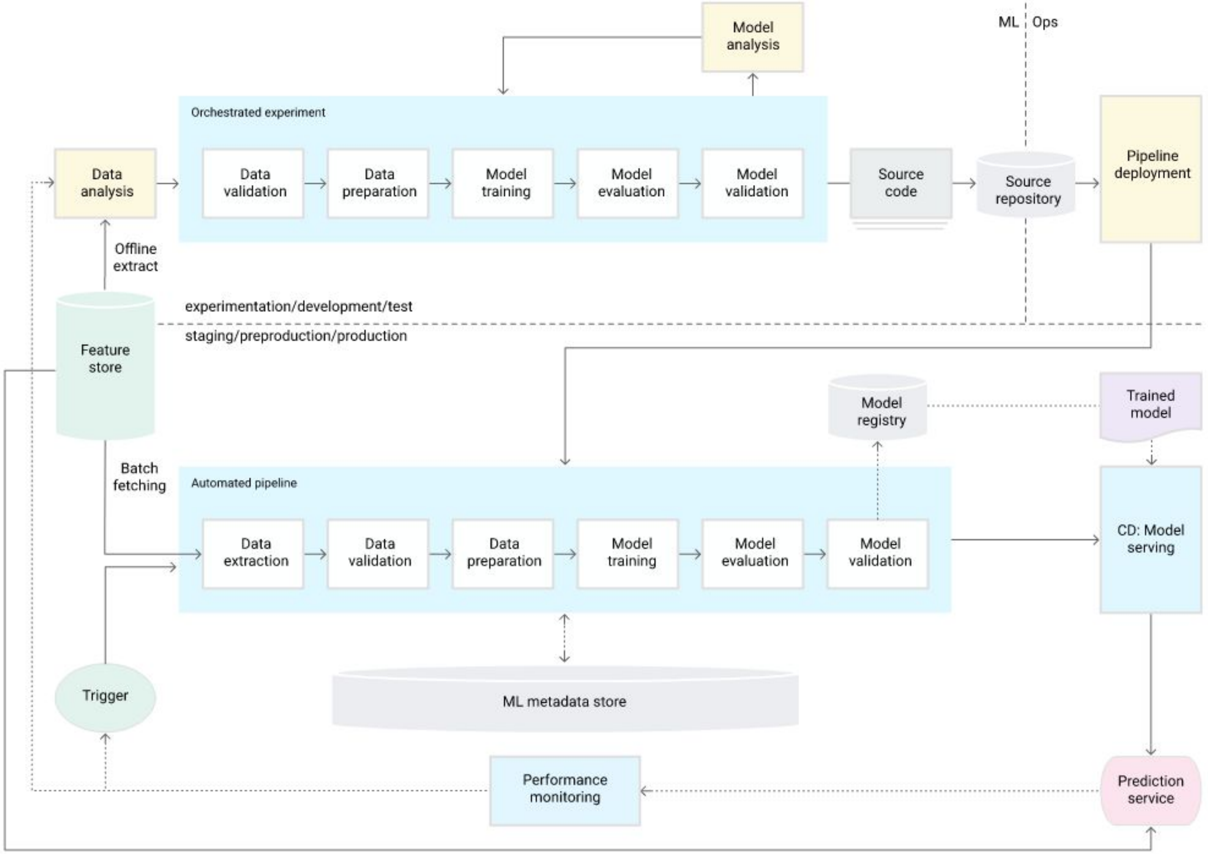


How are machine learning applications built and deployed?

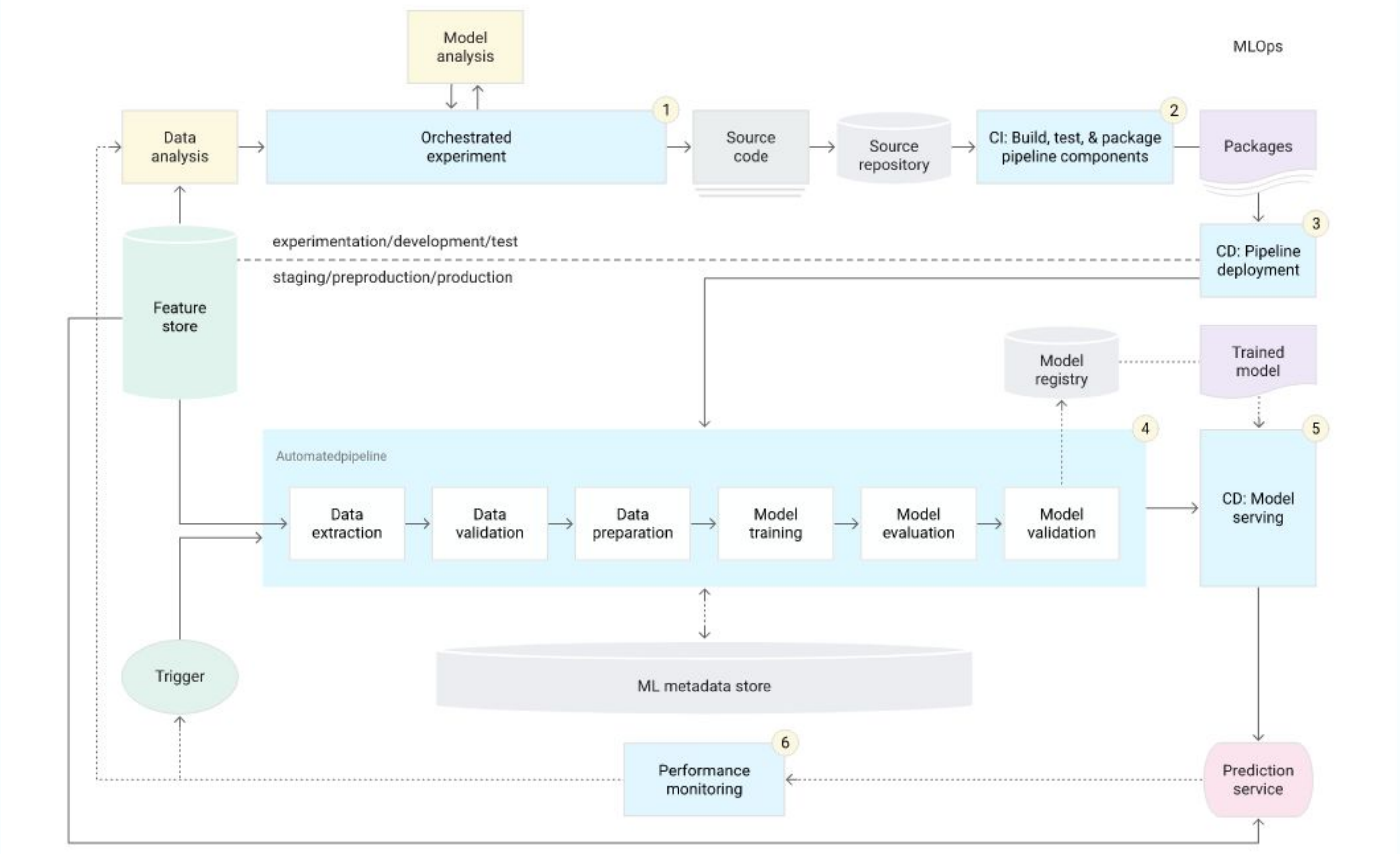
MLOps: Level 0



MLOps: Level 1

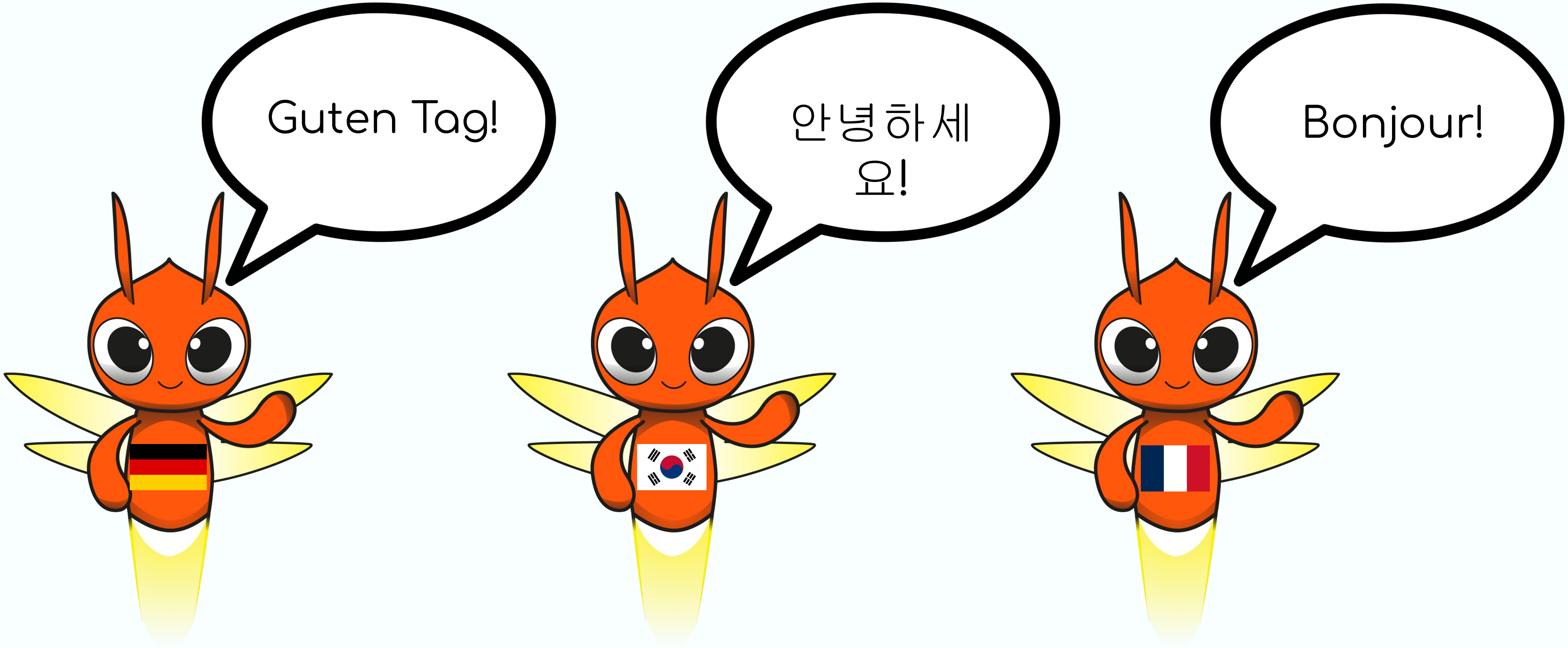


MLOps: Level 2

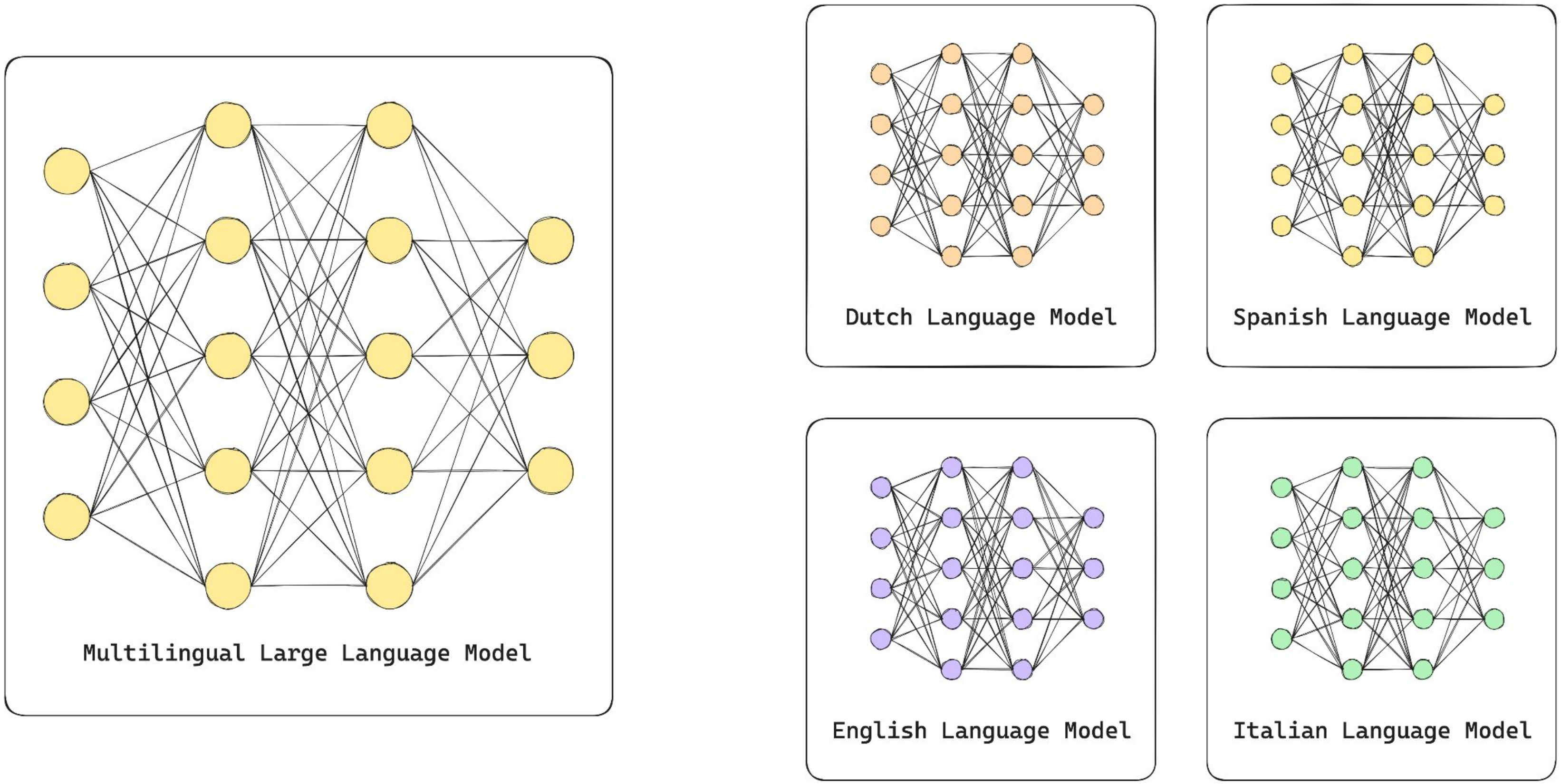


What is per entity training?

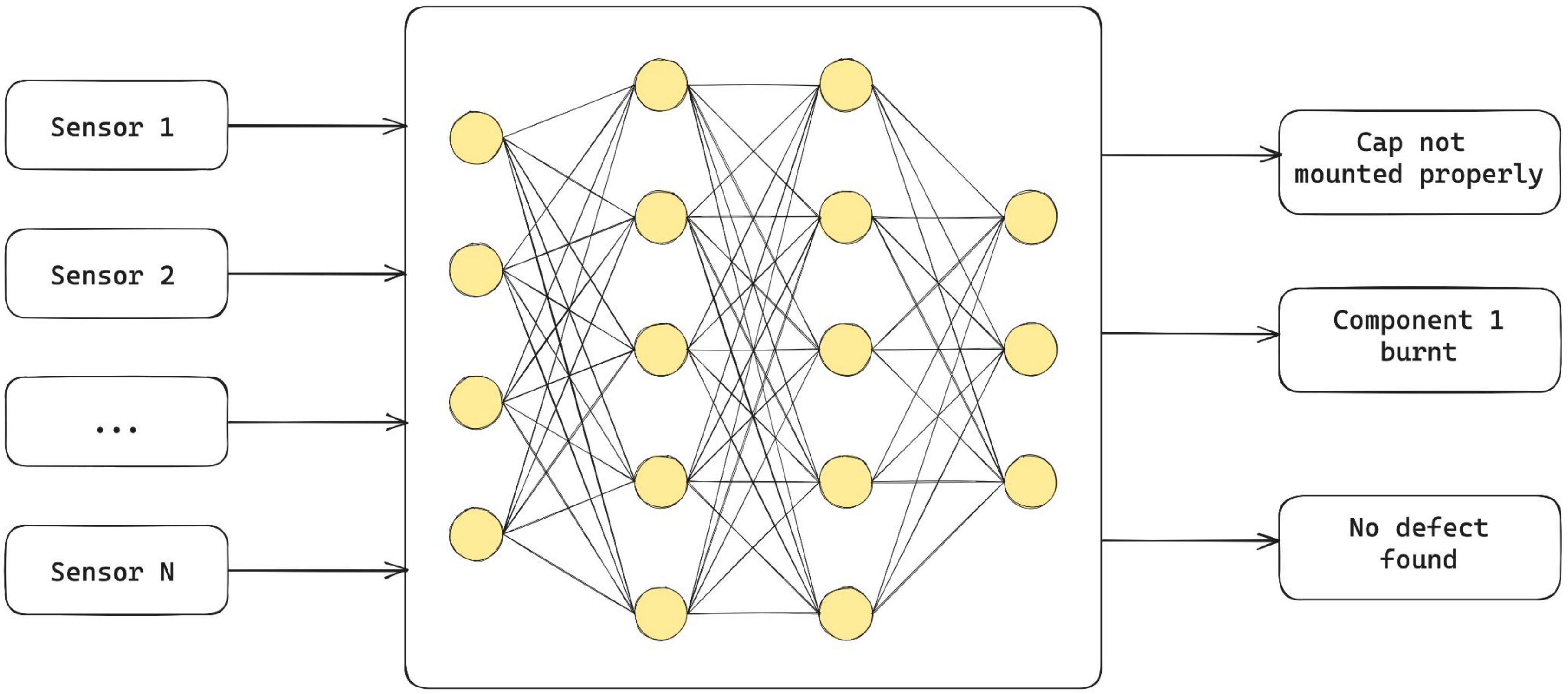
Example: Building multilingual chatbot



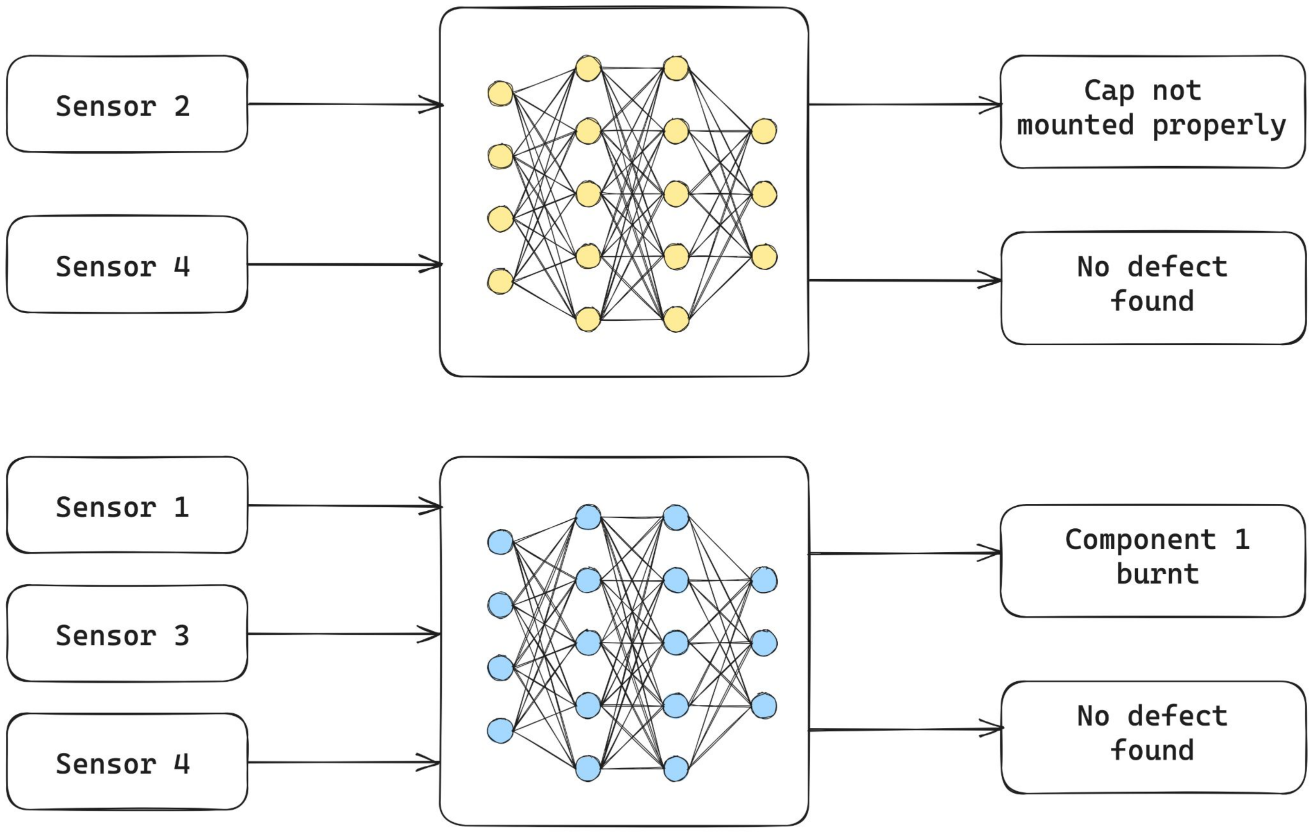
What is per entity training?



Example: Detect production defects using sensor data

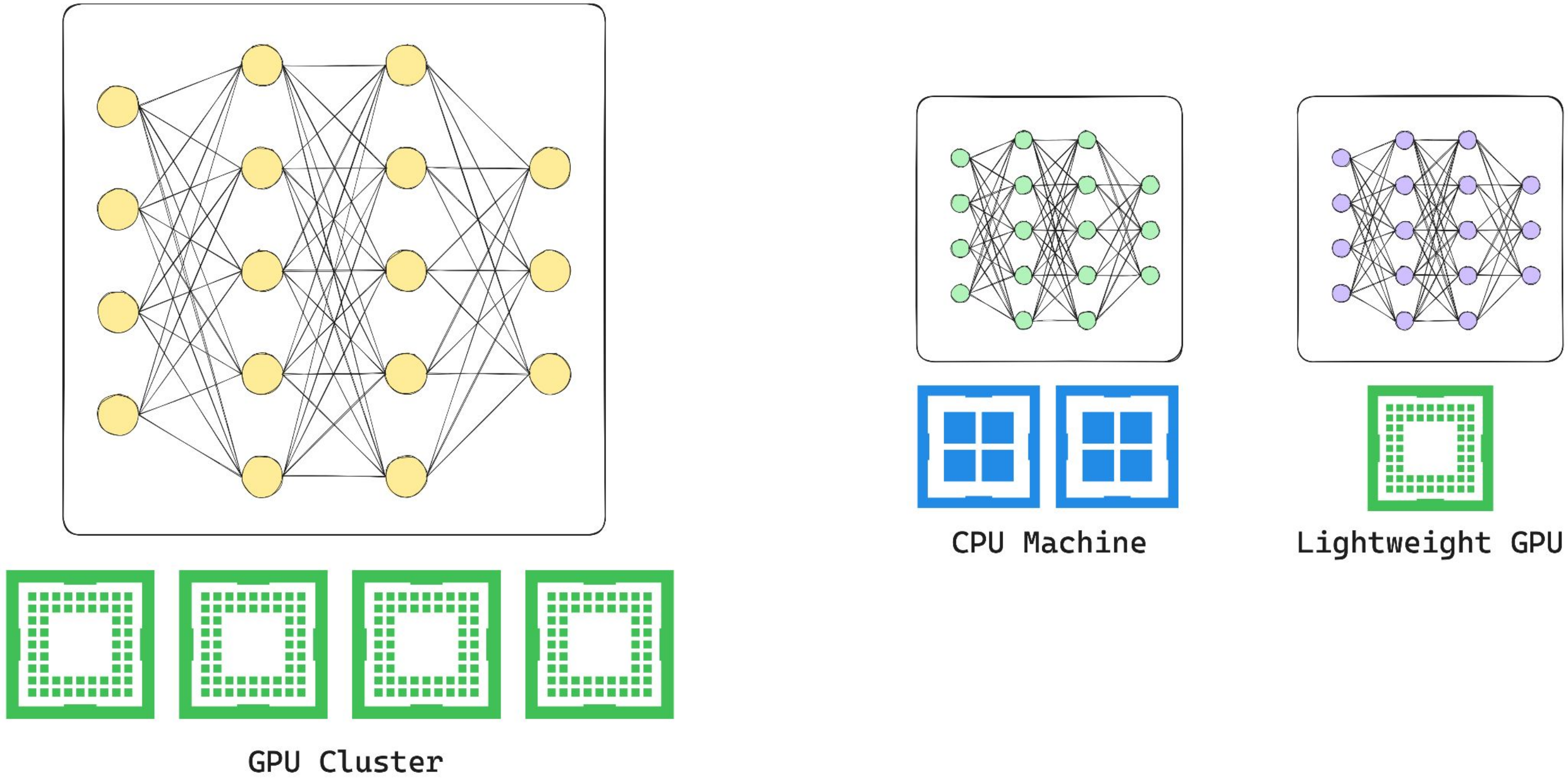


Example: Detect production defects using sensor data

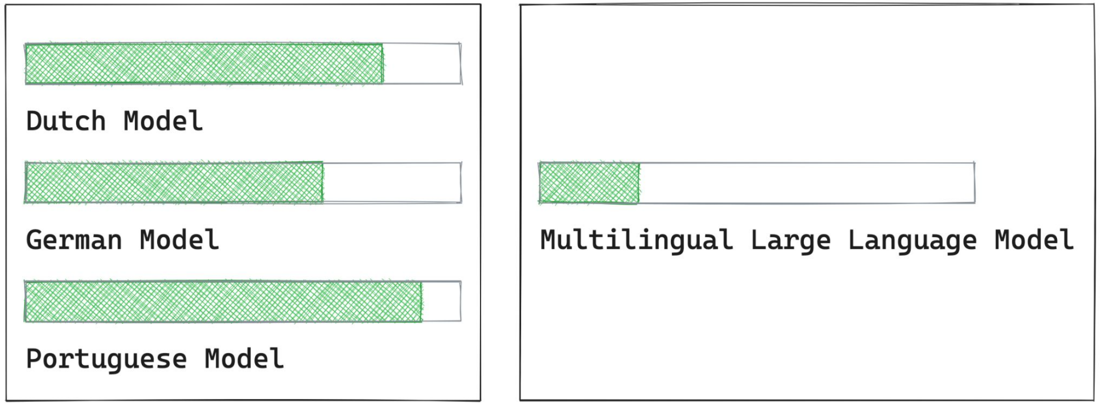


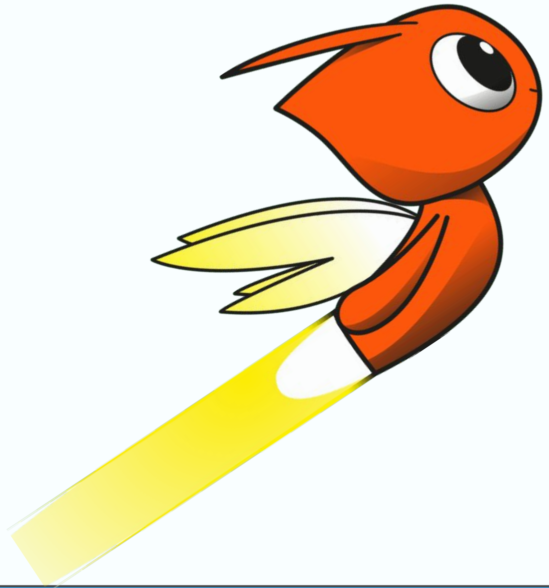
Why use a per entity strategy?

Reduce Model Infrastructure Requirements

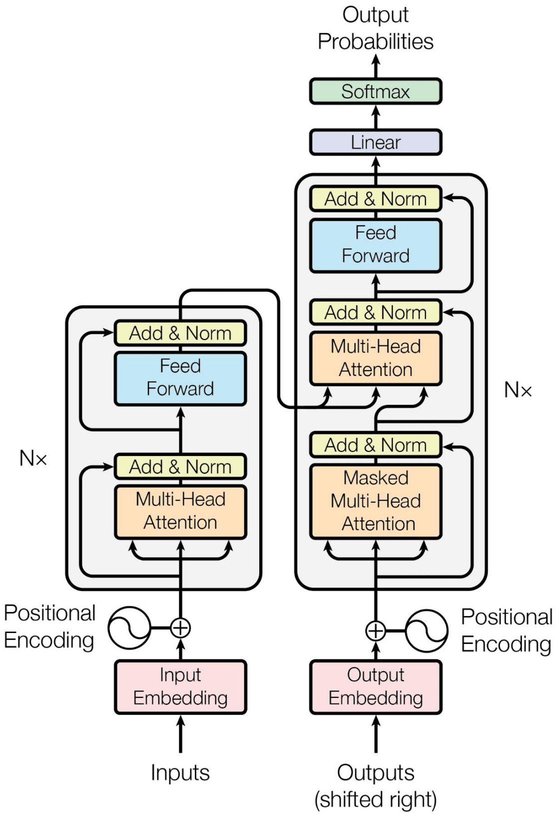


Faster training & inference

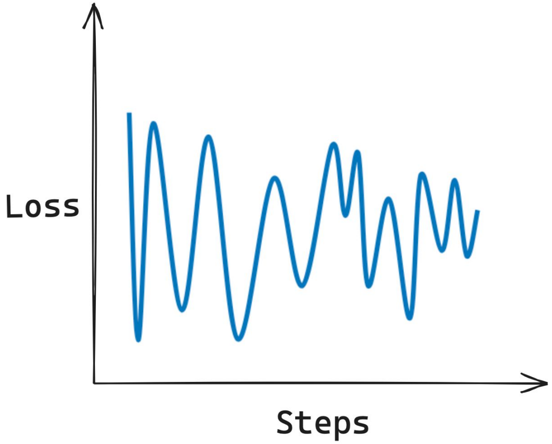




Address fairness and bias



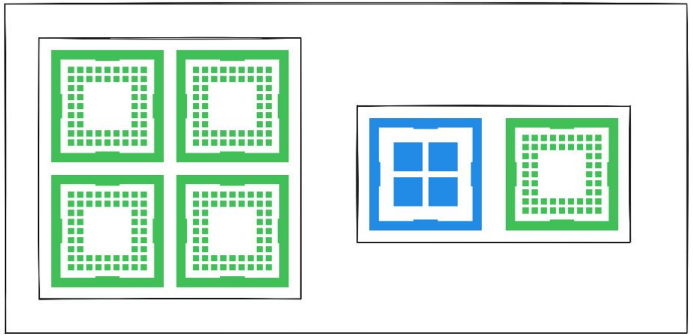
Easier to detect problems



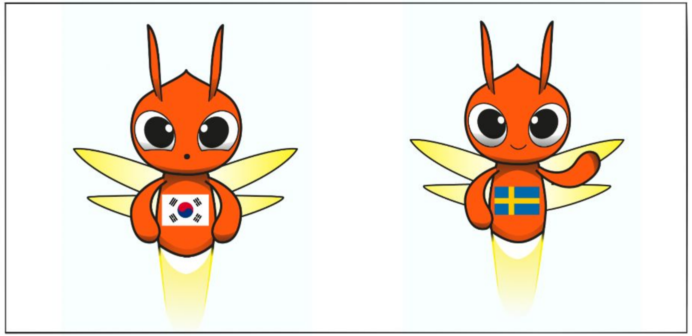
.25	.14	.36	.25
.35	.45	.08	.12
.12	.23	.33	.32
.28	.18	.23	.31

Confusion Matrix

Simpler models have the following advantages

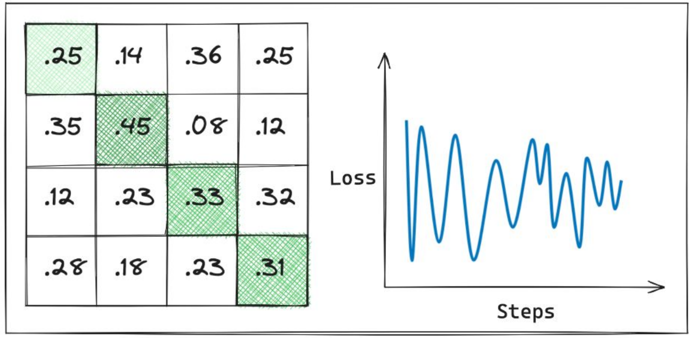


Less powerful hardware required



Easier to address bias

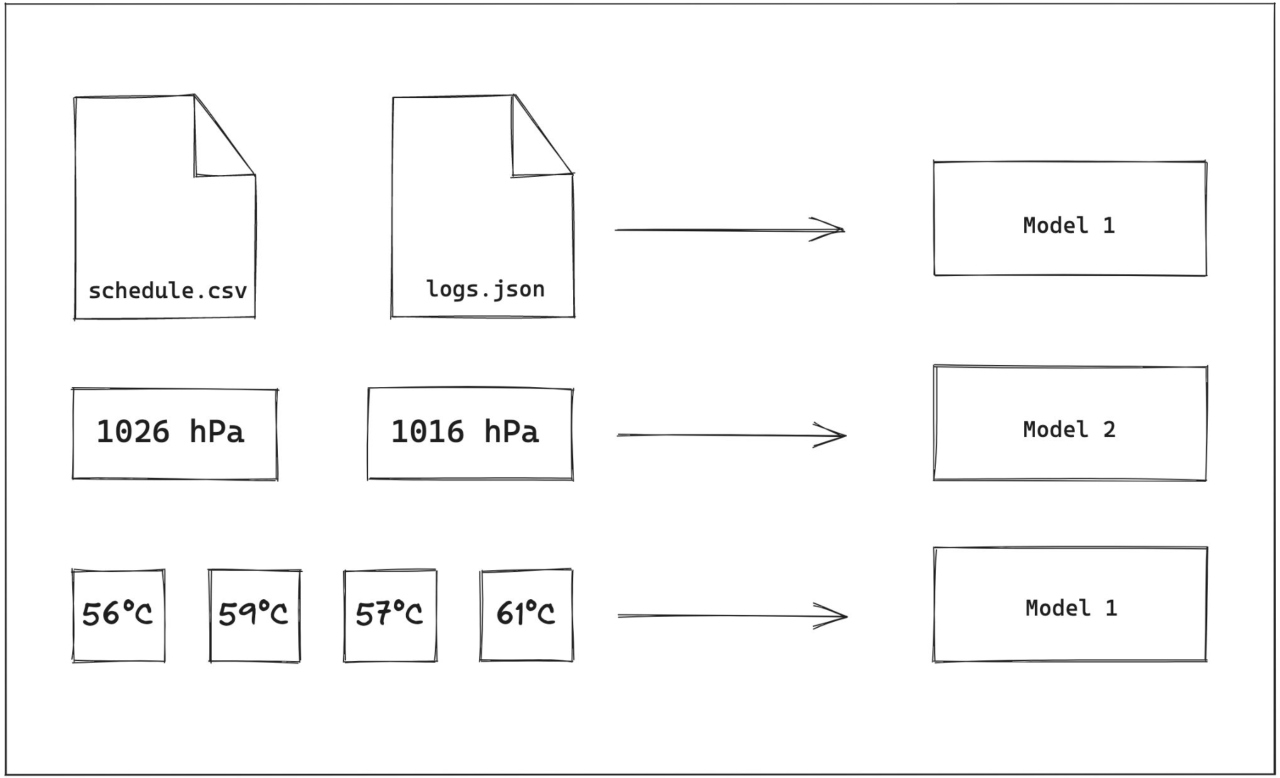
Faster training & inference



Easier debugging

But there is one big problem:
How do I manage the training of all of these models?

Manage training pipelines



The solution? Apache Beam!

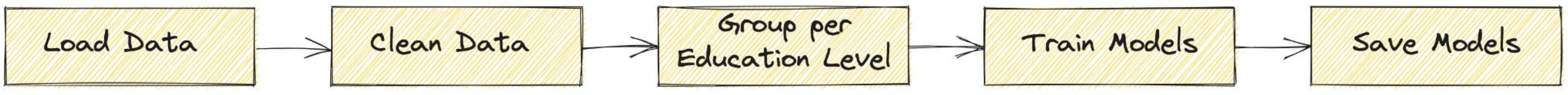
- Apache Beam can handle ***streaming*** and ***batch data***
- Apache Beam can easily ***prepare data*** for training
- Apache Beam can run on different ***runners*** depending on the model's ***requirements***
- ***Abstraction*** in ML libraries allows us to train models with few lines of code

Let’s look at an example of a per entity training pipeline

Predicting incomes per education level

Age	Workclass	Education	Marital Status	Occupation	Relationship	Race	Sex	Hours per Week	Native Country	Compensation
25	Private	11th	Never-married	Machine-op-inspct	Own-child	Black	Male	40	USA	<=50K.
38	Private	HS-grad	Married-civ-spouse	Farming-fishing	Husband	White	Male	50	USA	<=50K.
28	Local-gov	Assoc-acdm	Married-civ-spouse	Protective-serv	Husband	White	Male	40	USA	>50K.
44	Private	Some-college	Married-civ-spouse	Machine-op-inspct	Husband	Black	Male	40	USA	>50K.
18	?	Some-college	Never-married	?	Own-child	White	Female	30	USA	<=50K.

Pipeline overview



Split data per education level

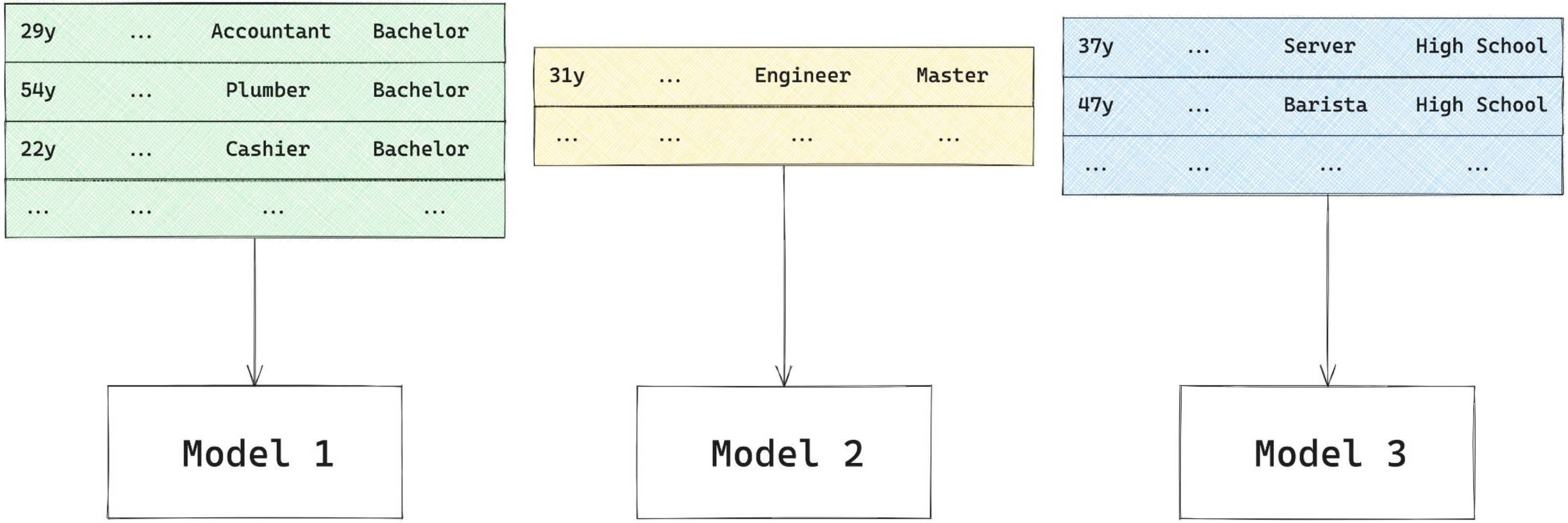
Age	...	Occupation	Education
29y	...	Accountant	Bachelor
31y	...	Engineer	Master
54y	...	Plumber	Bachelor
37y	...	Server	High School
47y	...	Barista	High School
22y	...	Cashier	Bachelor

29y	...	Accountant	Bachelor
54y	...	Plumber	Bachelor
22y	...	Cashier	Bachelor
...	...	...	...

31y	...	Engineer	Master
...	...	...	...

37y	...	Server	High School
47y	...	Barista	High School
...	...	...	...

Train model per dataset



Pipeline overview

```
with beam.Pipeline(options=pipeline_options) as pipeline:
    _ = (
        pipeline | "Read Data" >> beam.io.ReadFromText(known_args.input)
        | "Split data to make List" >> beam.Map(lambda x: x.split(','))
        | "Filter rows" >> beam.Filter(custom_filter)
        | "Create Key" >> beam.ParDo(CreateKey())
        | "Group by education" >> beam.GroupByKey()
        | "Prepare Data" >> beam.ParDo(PrepareDataforTraining())
        | "Train Model" >> beam.ParDo(TrainModel())
        | "Save" >> fileio.WriteToFiles(path=known_args.output,
sink=ModelSink()))
```

Step 1: Data preparation

```python
def custom_filter(element):
  return len(element) == 15 and '?' not in element \
       and ' Bachelors' in element or ' Masters' in element \
       or ' Doctorate' in element
```

Step 1: Data preparation

```
class PrepareDataforTraining(beam.DoFn):
  def process(self, element, *args, **kwargs):
    key, values = element

    #Convert to dataframe
    df = pd.DataFrame(values)
    last_ix = len(df.columns) - 1
    X, y = df.drop(last_ix, axis=1), df[last_ix]

    # select categorical and numerical features
    cat_ix = X.select_dtypes(include=['object', 'bool']).columns
    num_ix = X.select_dtypes(include=['int64', 'float64']).columns

    # label encode the target variable to have the classes 0 and 1
    y = LabelEncoder().fit_transform(y)

    yield (X, y, cat_ix, num_ix, key)
```

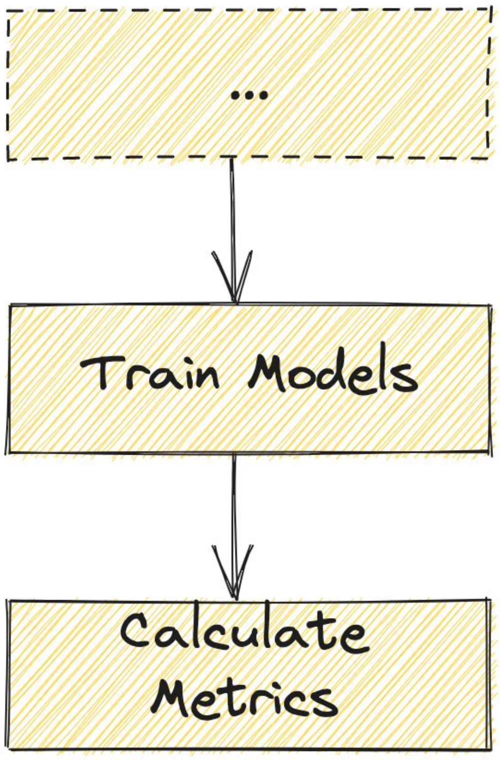
Step 2: Training the models

```python
class TrainModel(beam.DoFn):

  def process(self, element, *args, **kwargs):
    X, y, cat_ix, num_ix, key = element
    steps = [('c', OneHotEncoder(handle_unknown='ignore'), cat_ix),
             ('n', MinMaxScaler(), num_ix)]

    # one hot encode categorical, normalize numerical
    ct = ColumnTransformer(steps)

    # wrap the model in a pipeline
    pipeline = Pipeline(steps=[('t', ct), ('m', DecisionTreeClassifier())])
    pipeline.fit(X, y)

    yield (key, pipeline)
```

Step 3: Saving models

```python
class ModelSink(fileio.FileSink):
  def open(self, fh):
    self._fh = fh

  def write(self, record):
    _, trained_model = record
    pickled_model = pickle.dumps(trained_model)
    self._fh.write(pickled_model)

  def flush(self):
    self._fh.flush()
```

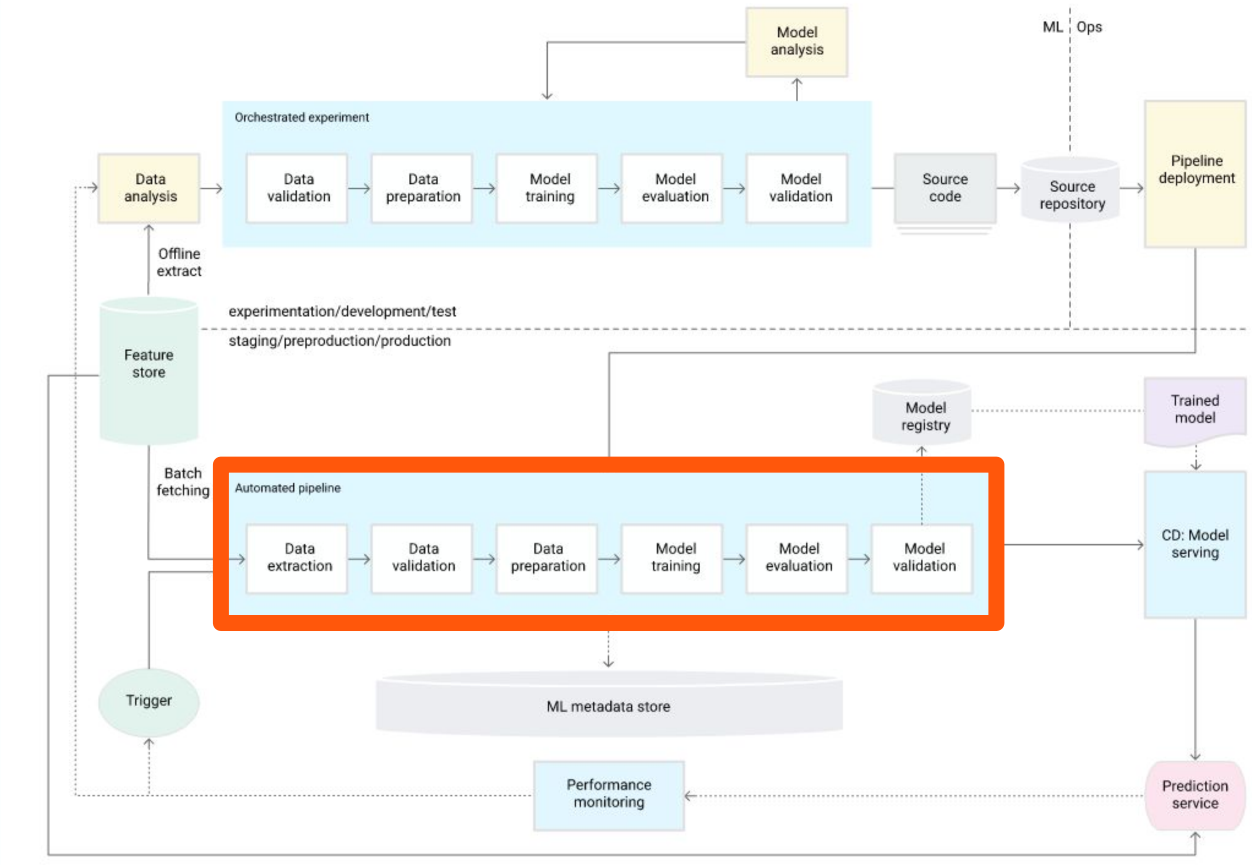
Extending the pipeline



Extending pipeline with metrics

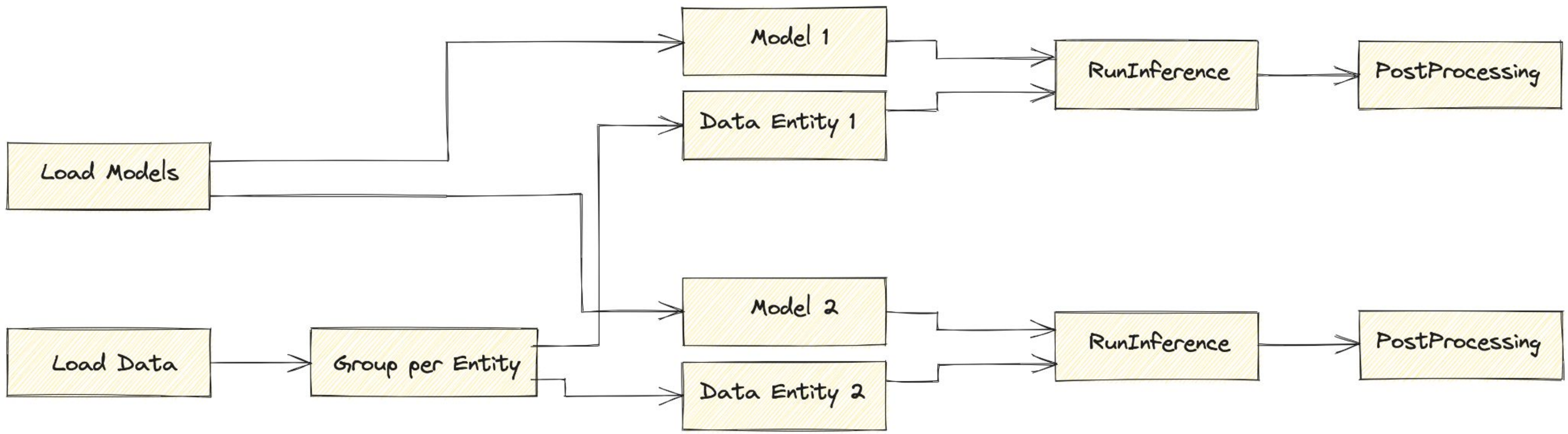
```
class EvaluateModel(beam.DoFn):
  def __init__(self, model_uri):
    file = FileSystems.open(model_uri, 'rb')
    self.model = pickle.load(file)

  def process(self, element, *args, **kwargs):
    inputs, labels = element
    predictions = self.model.predict(inputs)
    accuracy = sklearn.metrics.accuracy_score(y_pred=predictions,
y_true=labels)
    f1 = sklearn.metrics.f1_score(y_pred=predictions, y_true=labels)
    recall = sklearn.metrics.recall_score(y_pred=predictions, y_true=labels)

    file = FileSystems.open(f'model_uri_metrics', 'web')
    file.writelines([f'accuracy: {accuracy}', f'f1: {f1}', f'recall:
{recall}'])
```

How does this pipeline fit in the MLOps architecture?



Let's try out our model using the RunInference trasform

Bonus: Inference in Apache Beam



Summary

- Apache Beam is more and more becoming technology that can be used in advanced MLOps setups
- Per entity strategy has several advantages
    - Requires less powerful hardware
    - Faster training and inference
    - Easier to address bias
    - Easier to debug
- Apache Beam a perfect candidate for per entity training pipelines thanks to
    - Excellent for data preprocessing and preparation
    - Different runners depending on model requirements
    - Abstraction in ML libraries that make it easy to train a model

Jasper Van den Bossche

QUESTIONS?

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https://github.com/jaxpr
https://www.ml6.eu/