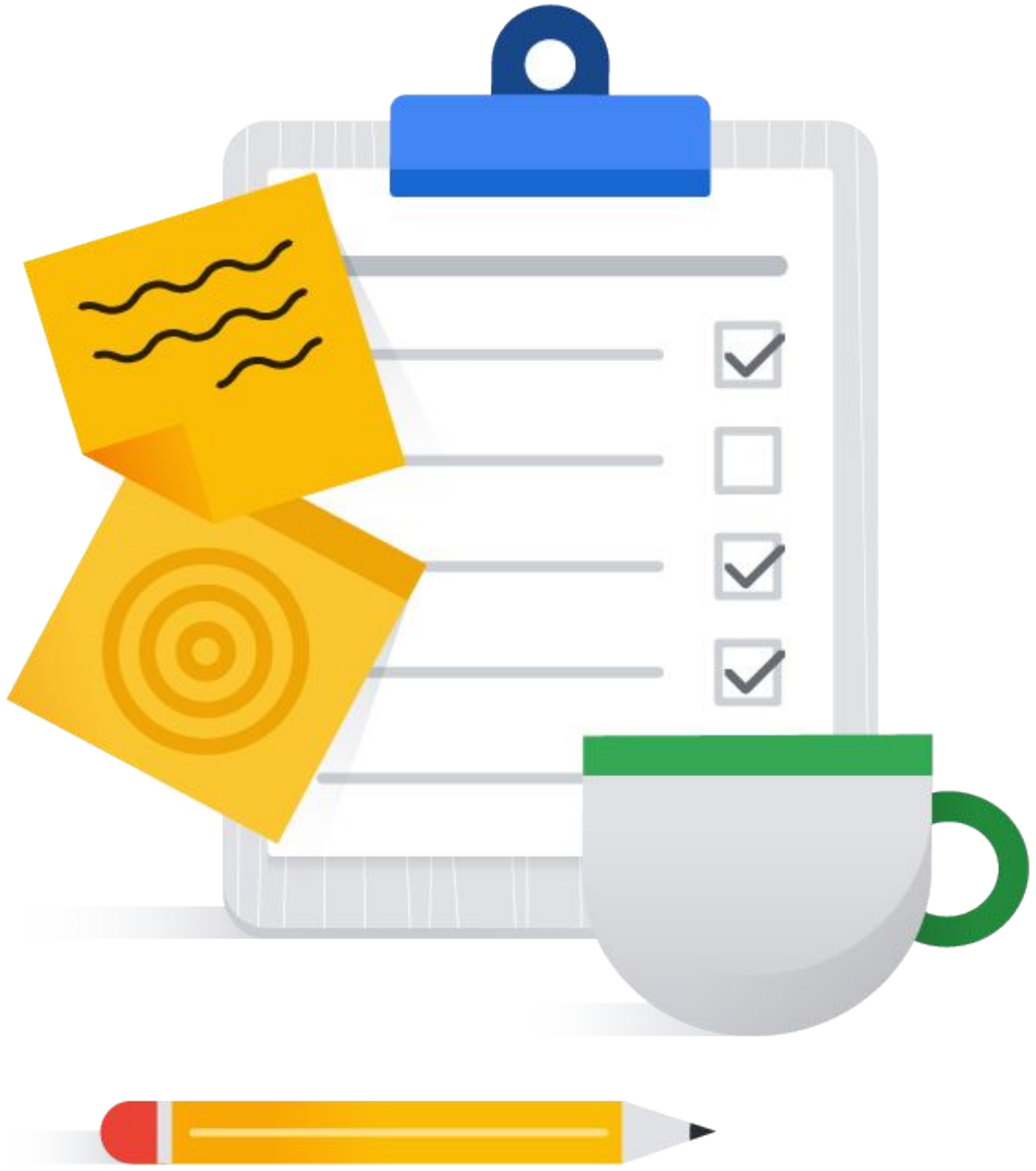
03

Serverless Data Processing with Dataflow

Serverless Data Processing with Dataflow

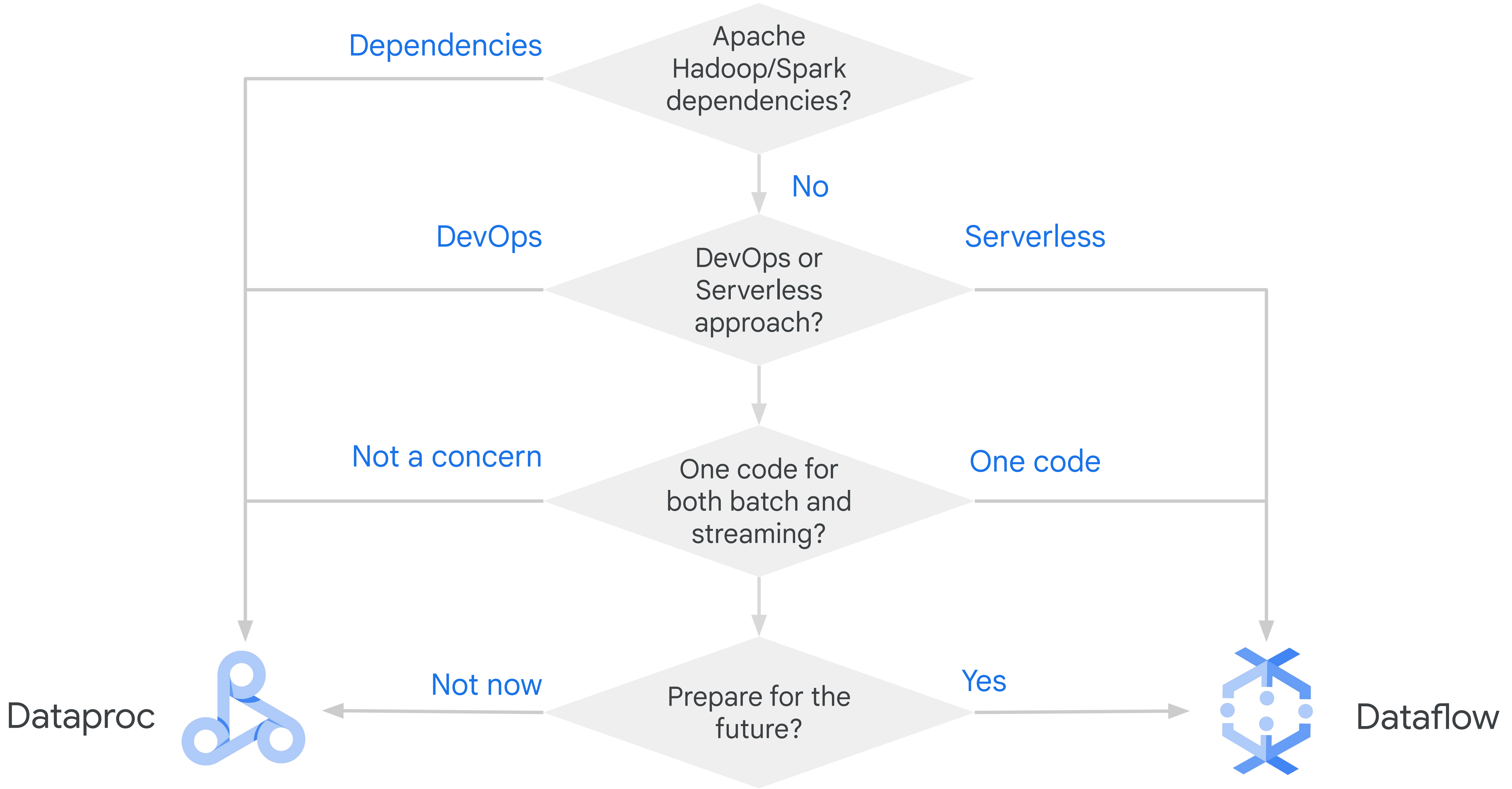


Serverless Data Processing with Dataflow

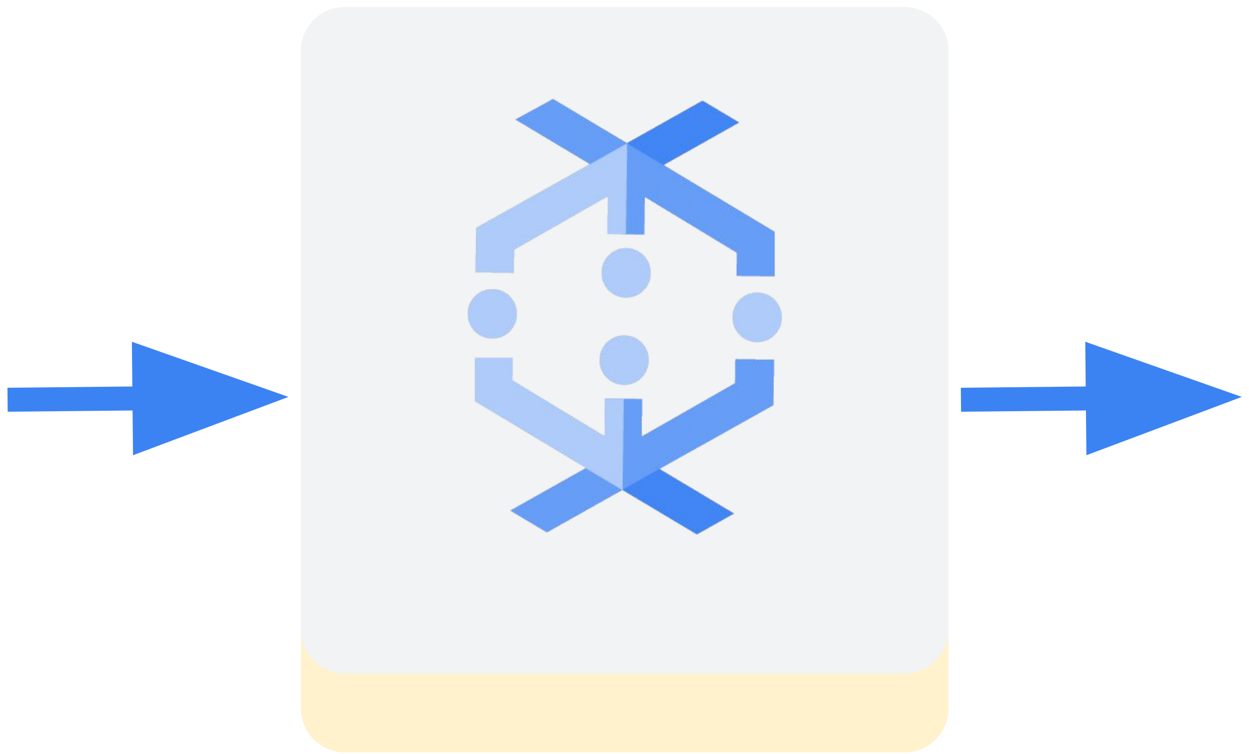
Dataflow versus Dataproc

	Dataflow	Dataproc
Recommended for:	New data processing pipelines, unified batch and streaming	Existing Hadoop/Spark applications, machine learning/data science ecosystem, large-batch jobs, preemptible VMs
Fully-managed:	Yes	No
Auto-scaling:	Yes, transform-by-transform (adaptive)	Yes, based on cluster utilization (reactive)
Expertise:	Apache Beam	Hadoop, Hive, Pig, Apache Big Data ecosystem, Spark, Flink, Presto, Druid

Choosing between Dataflow and Dataproc



Dataflow



Qualities that Dataflow contributes to data engineering solutions:

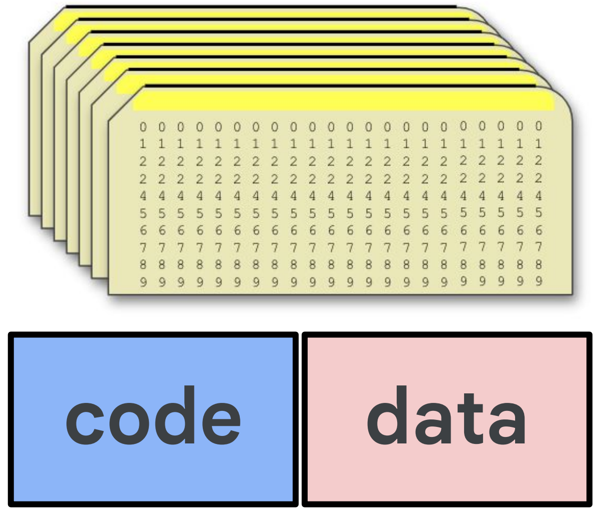
- Scalability
- Low latency

Batch programming and data processing used to be two very separate and different things

Batch programming

1940's

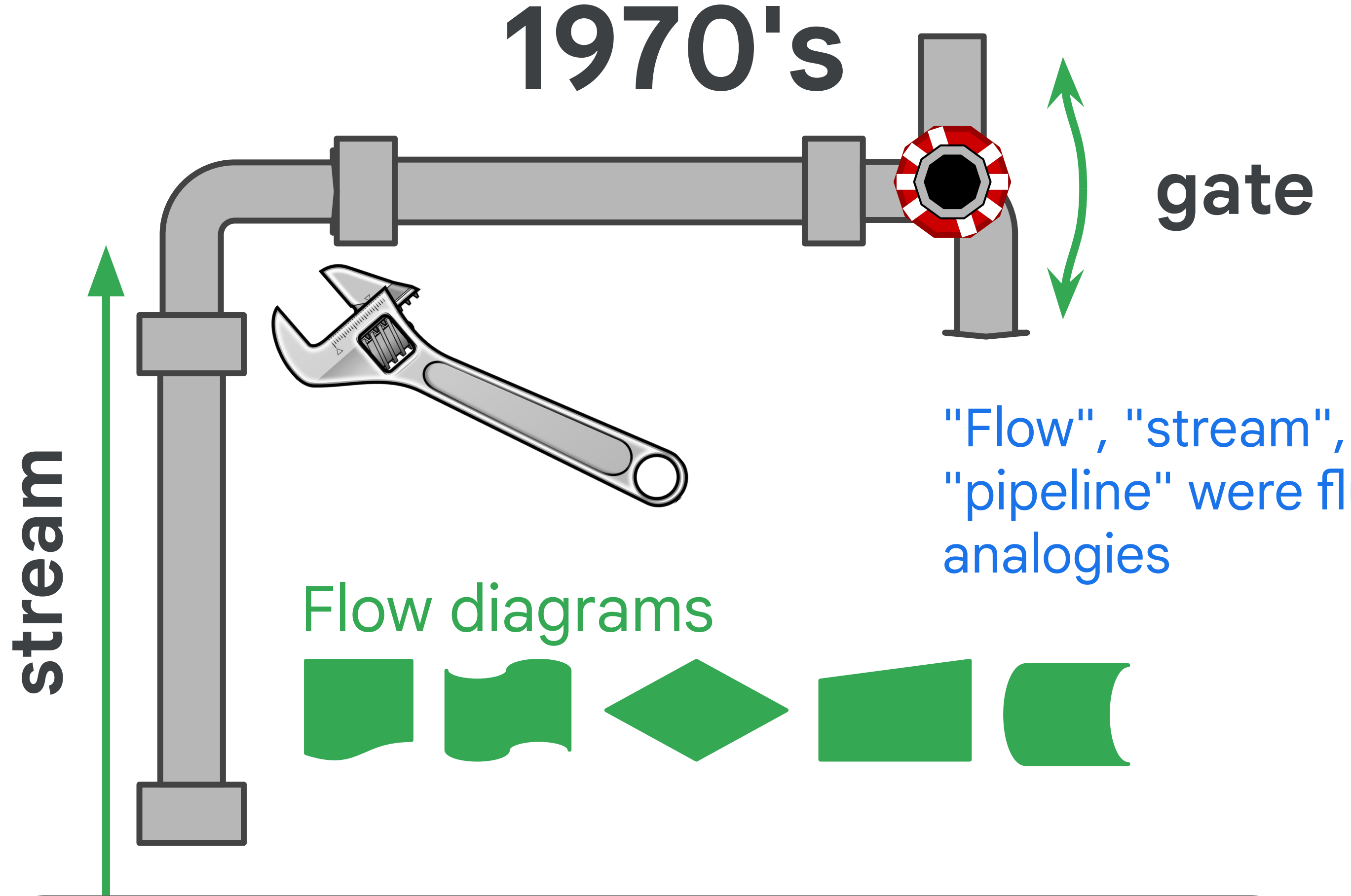
"Batch" originally referred to a batch or box of punch-cards



Von Neumann architecture

Data processing

1970's

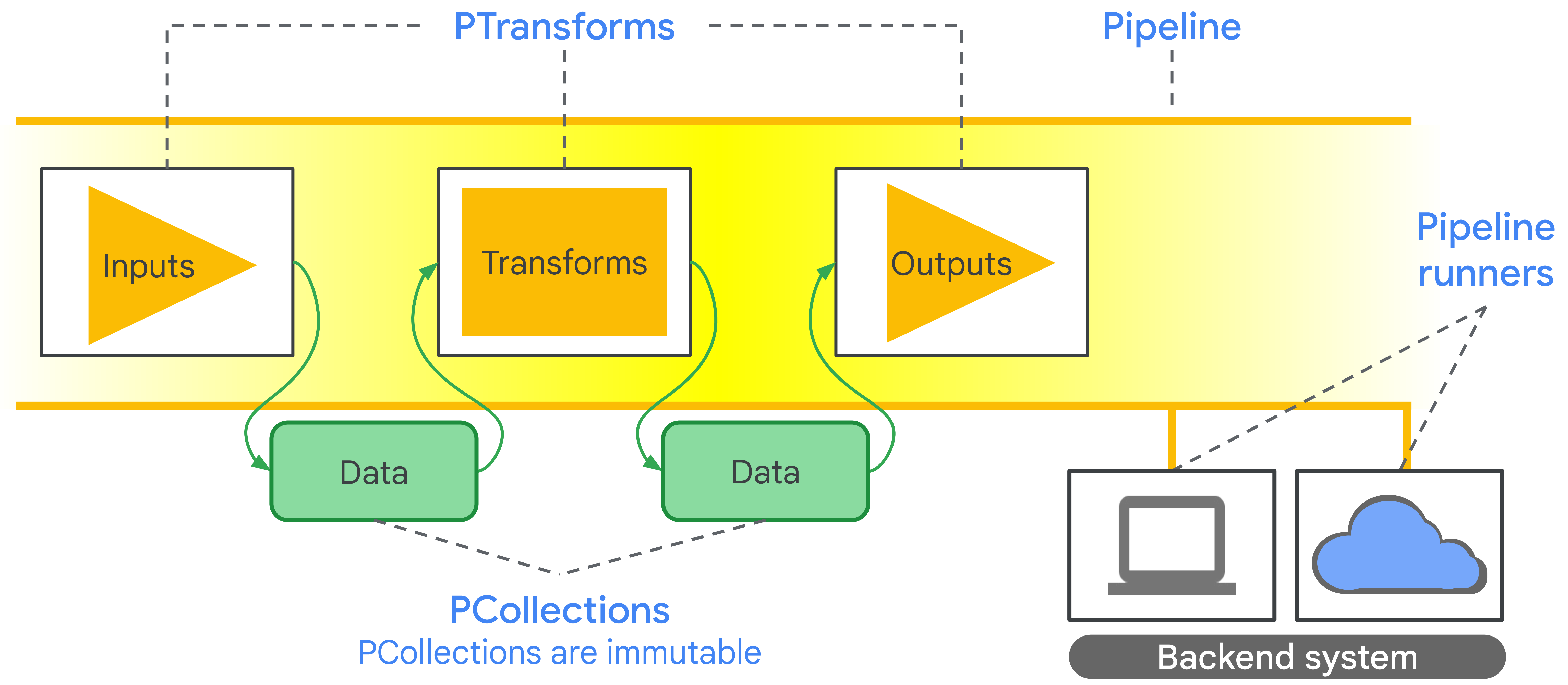


"Flow", "stream", and "pipeline" were fluid analogies

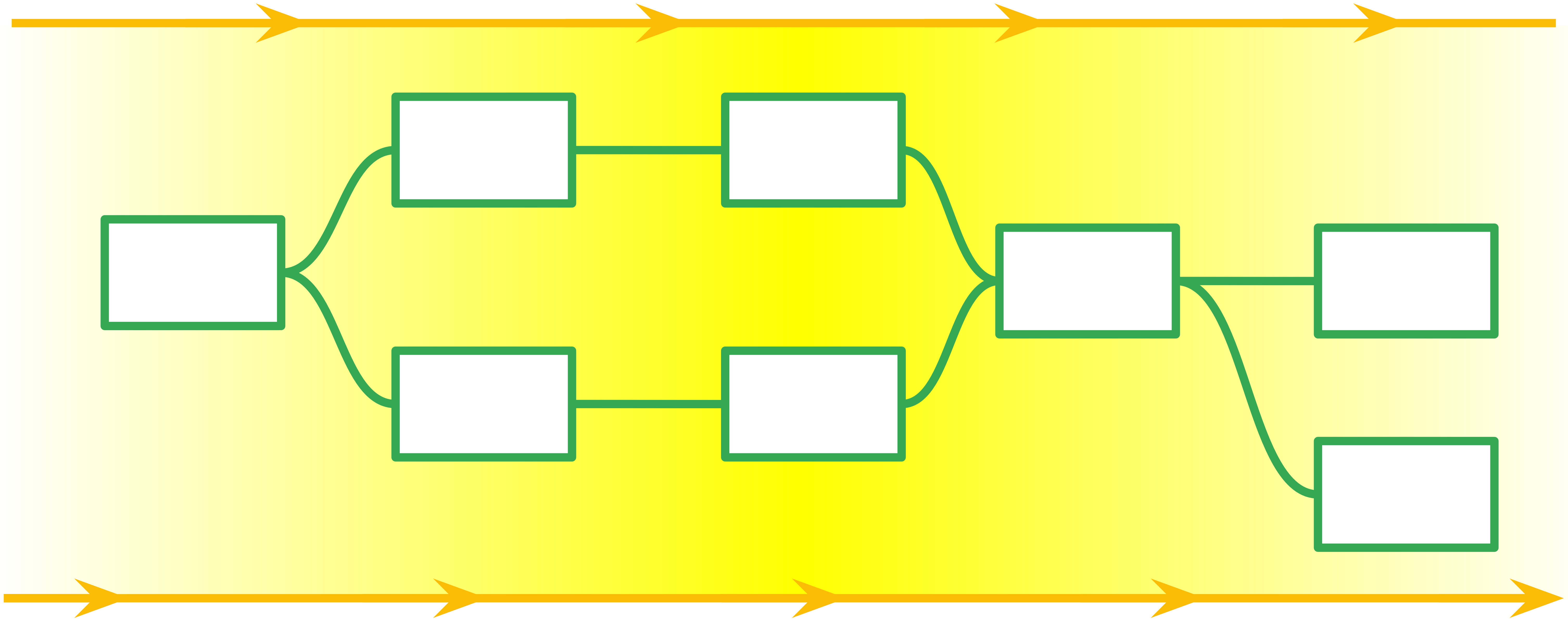
Dataflow architecture

Different tools, different platforms, different concepts, different methods.

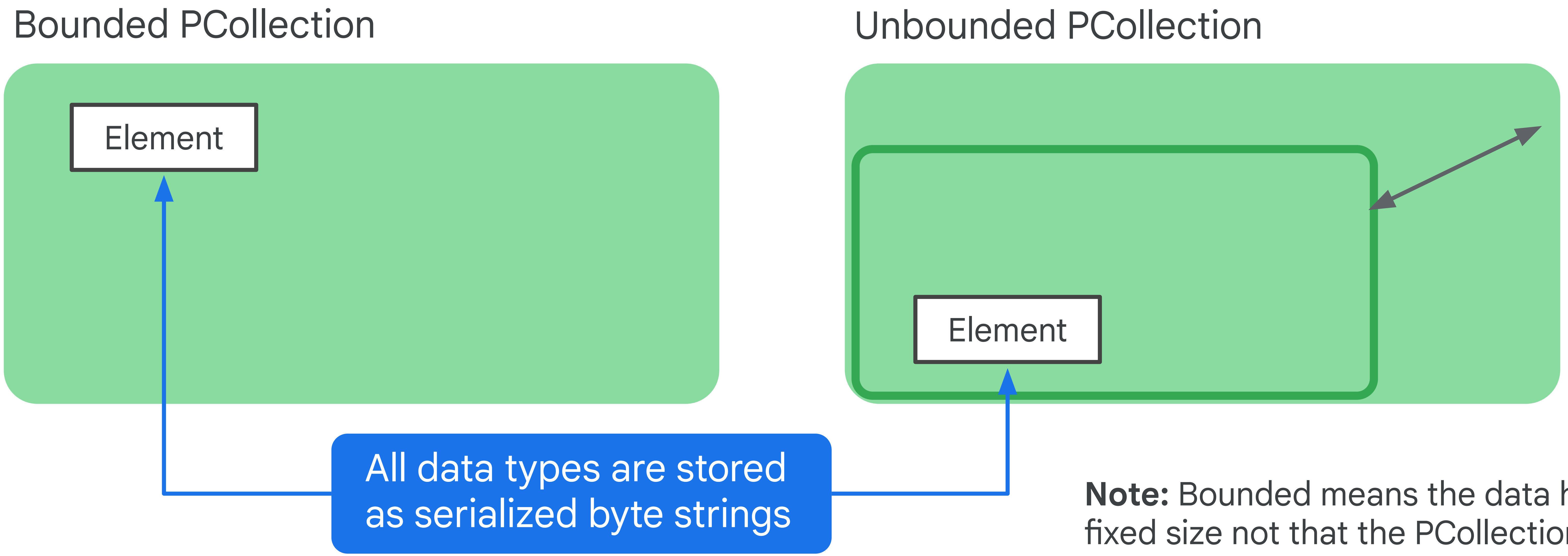
Apache BEAM = Batch + strEAM



A Dataflow pipeline is a directed graph of steps



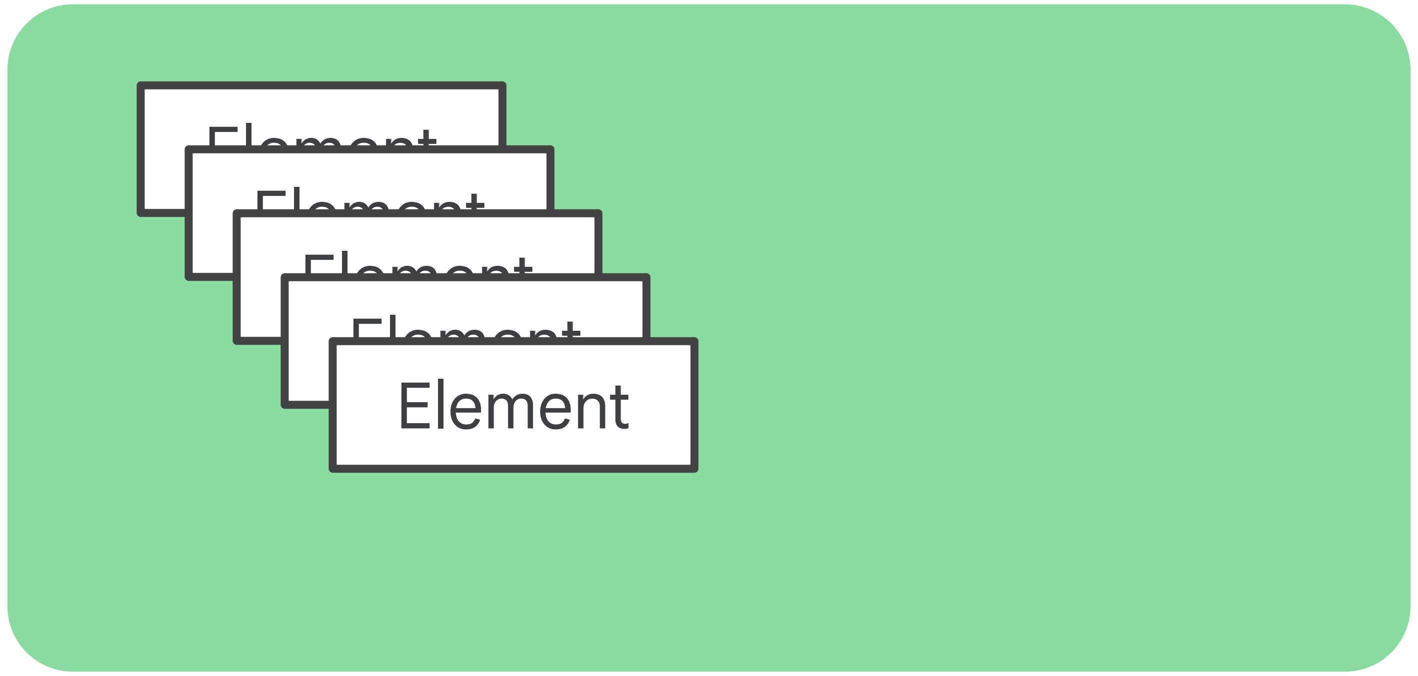
A PCollection represents batch or stream data



Note: Bounded means the data has a fixed size not that the PCollection size is limited. A PCollection can be any size and be distributed across many workers.

Each PCollection element can be distributed for parallel processing

Bounded PCollection



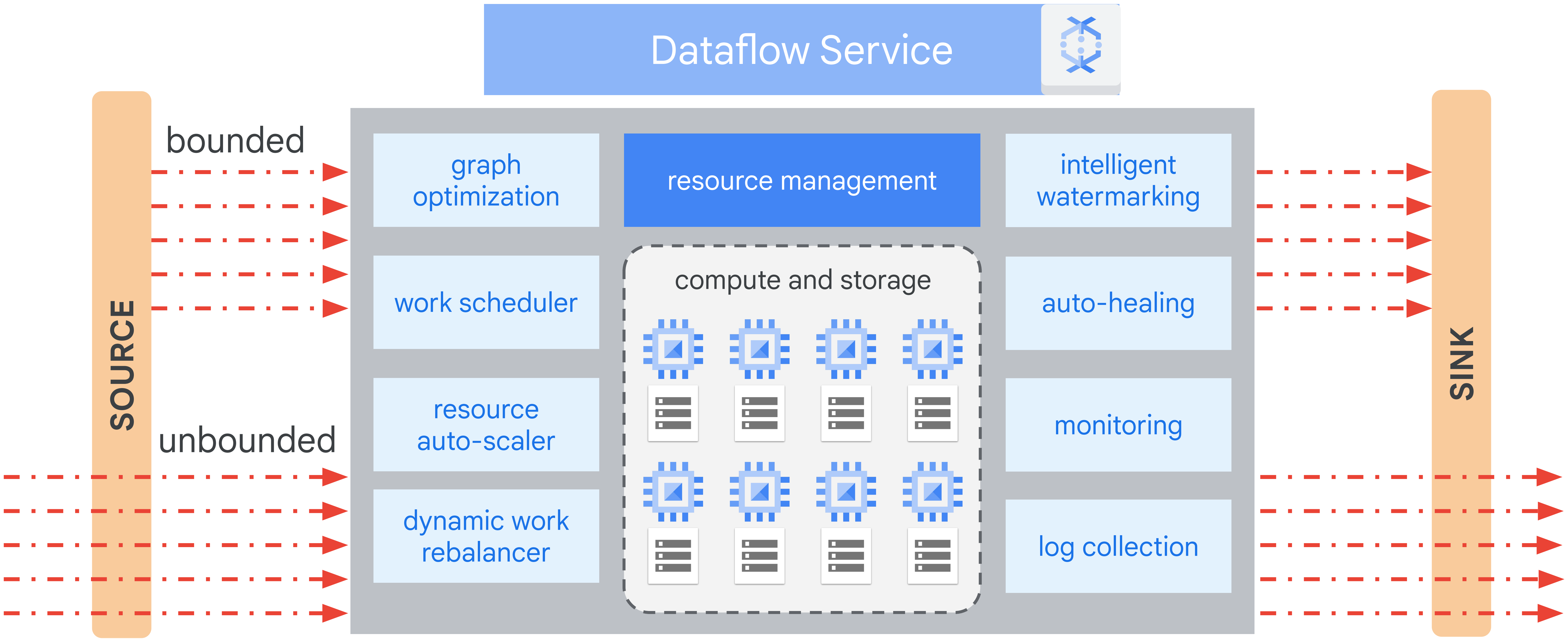
Unbounded PCollection

All data types are stored as serialized byte strings

Note: Bounded means the data has a fixed size not that the PCollection size is limited. A PCollection can be any size and be distributed across many workers.

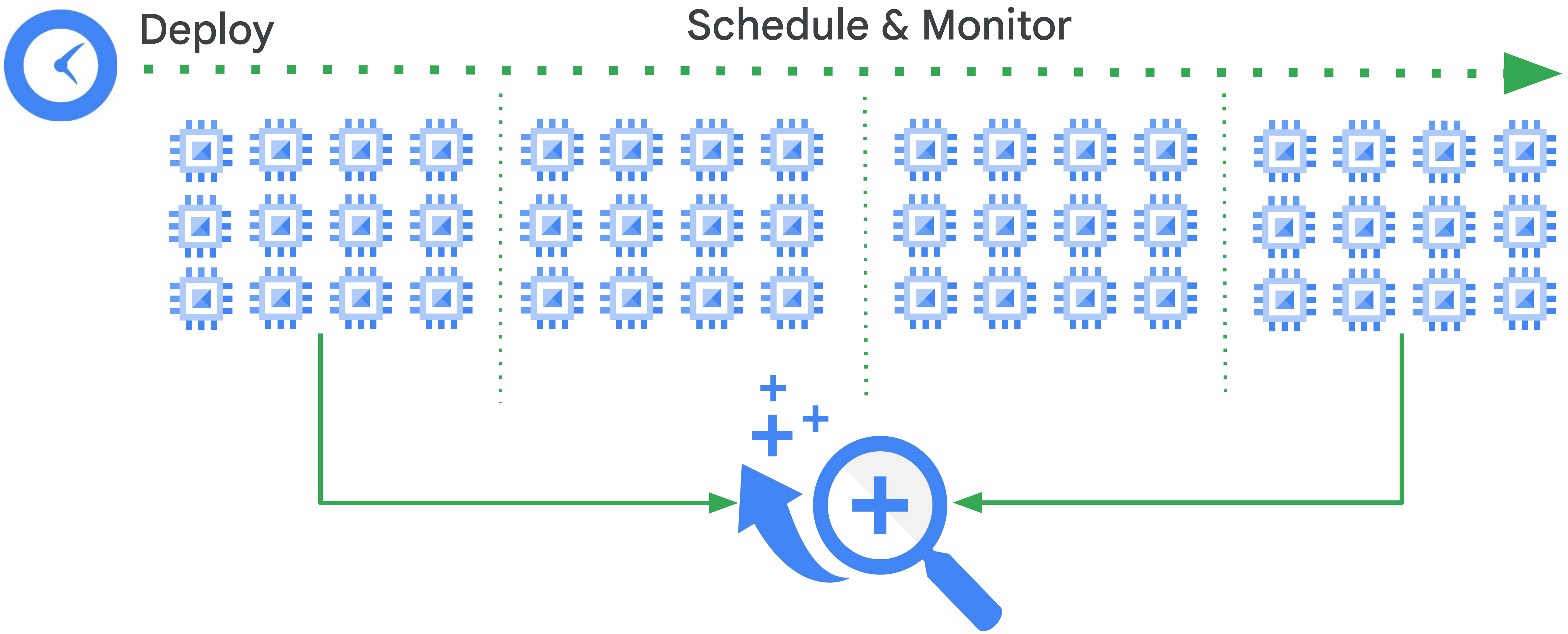
Serverless Data Processing with Dataflow

How does Dataflow work?

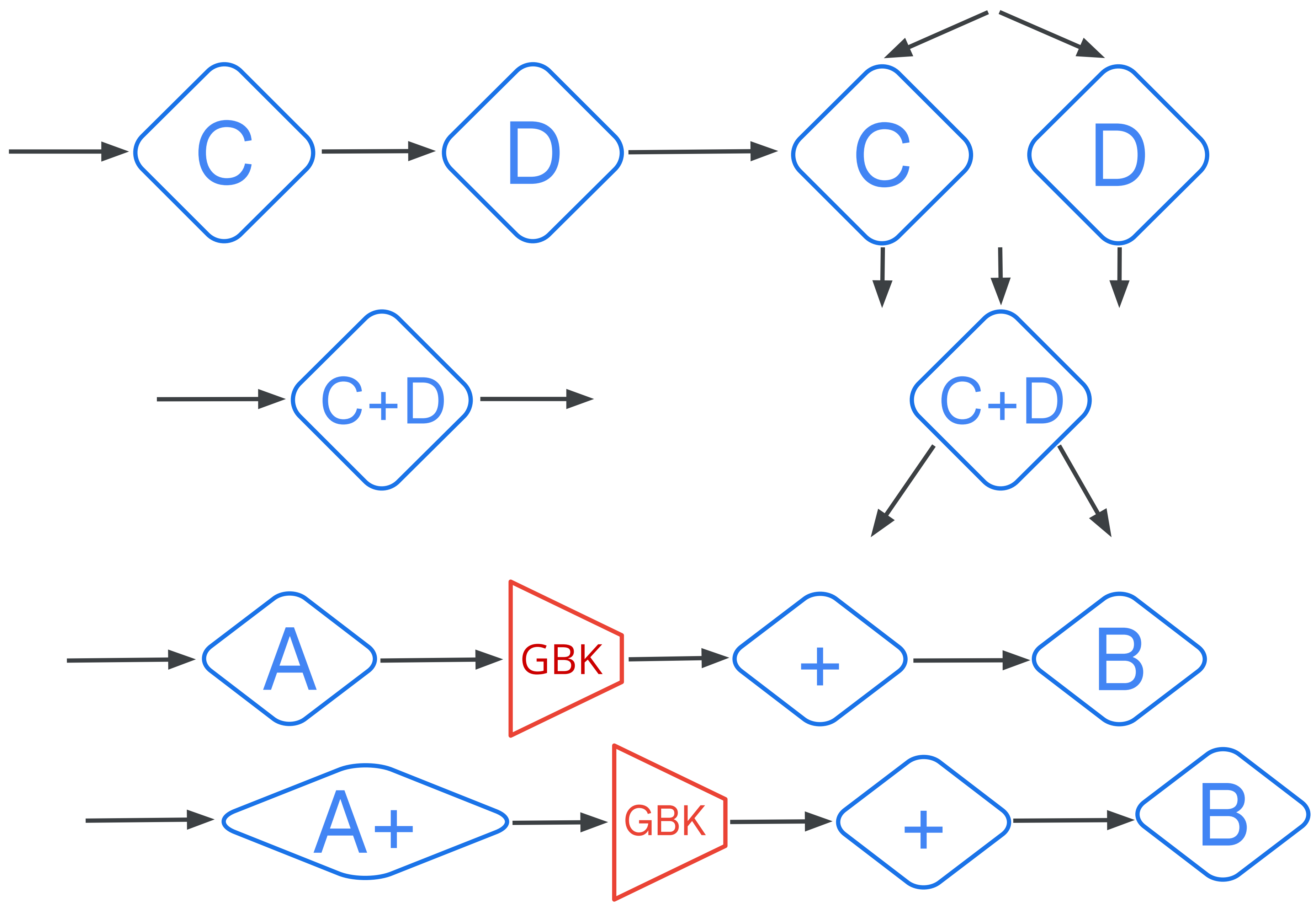


Dataflow constantly rebalances the work.

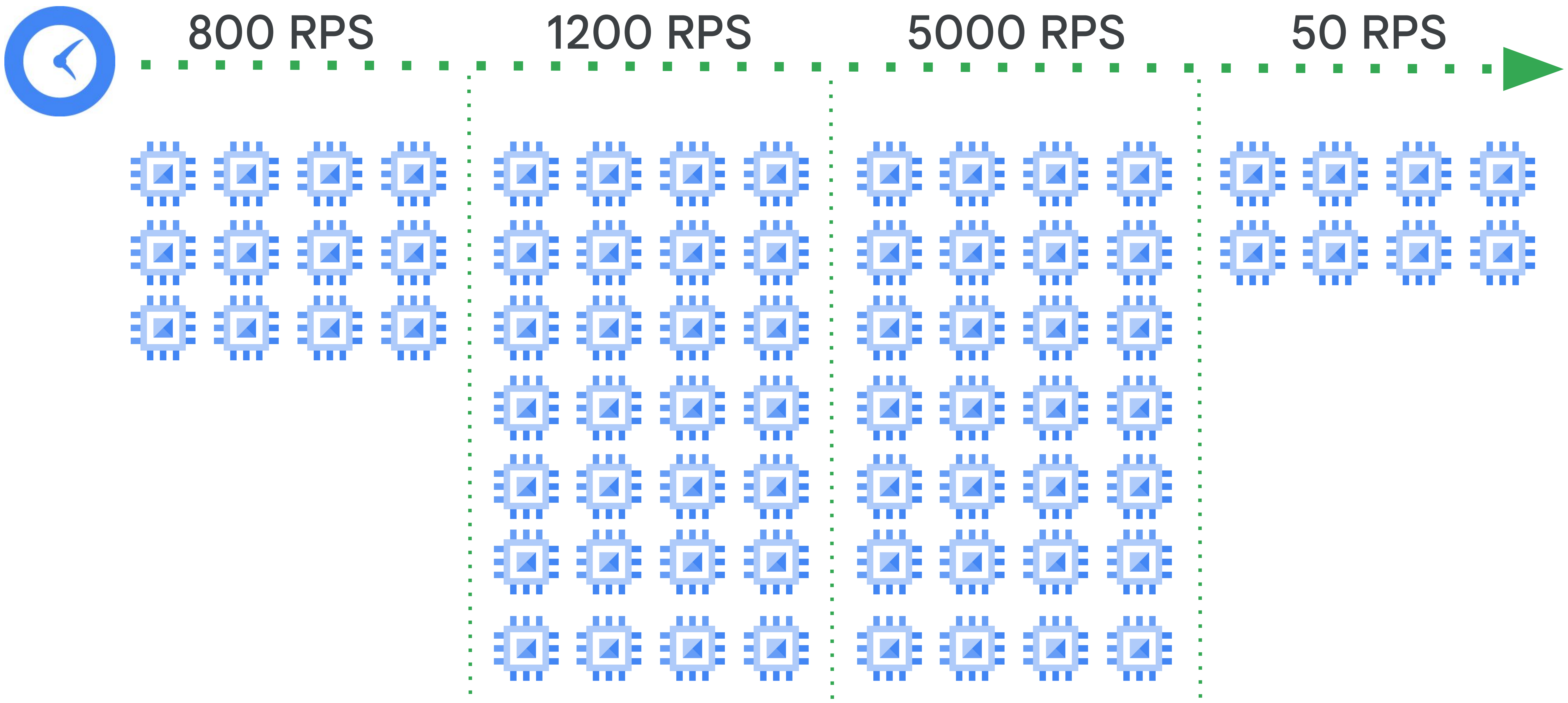
Why customers value Dataflow: Fully-managed and auto-configured



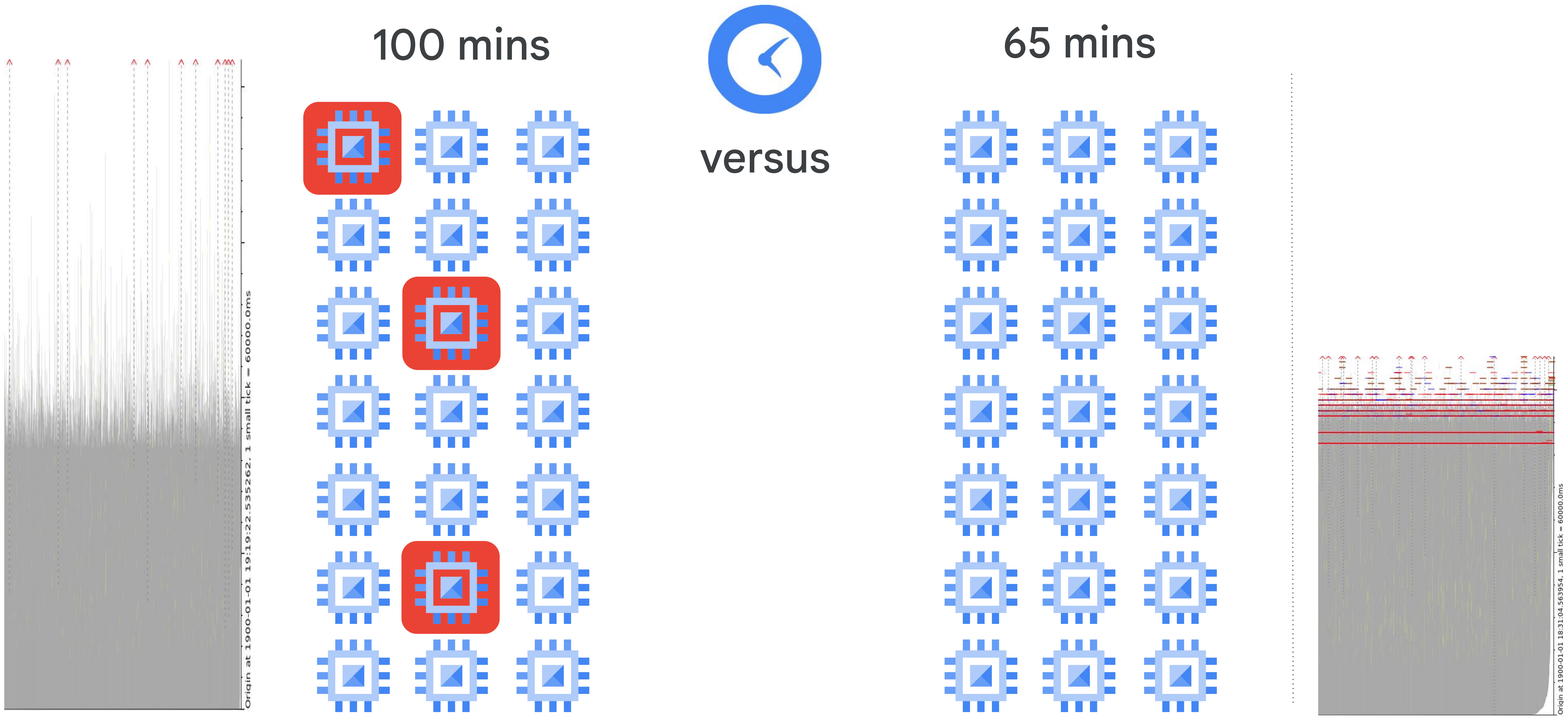
Why customers value Dataflow: Graph is optimized for best execution path



Why customers value Dataflow: Autoscaling mid-job



Why customers value Dataflow: Dynamic work rebalancing mid-job

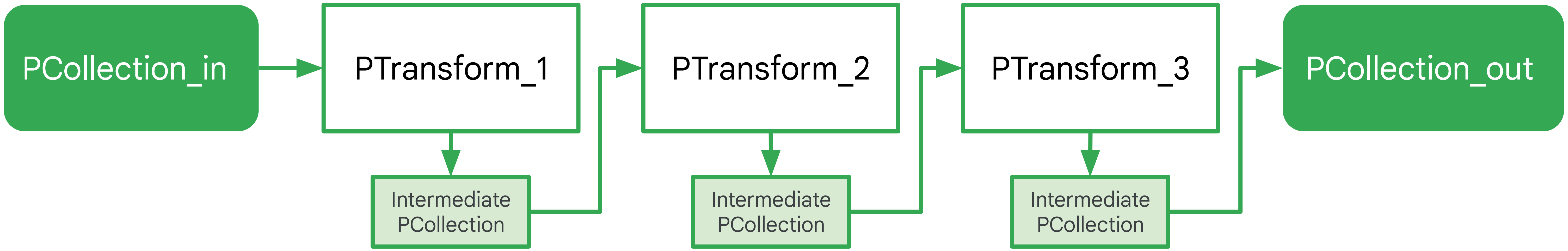


Why customers value Dataflow: Strong streaming semantics

- Exactly once aggregations
- Rich time tracking
- Good integration with other Google Cloud services

Serverless Data Processing with Dataflow

How to construct a simple pipeline



Python

Python overloads the pipe operator

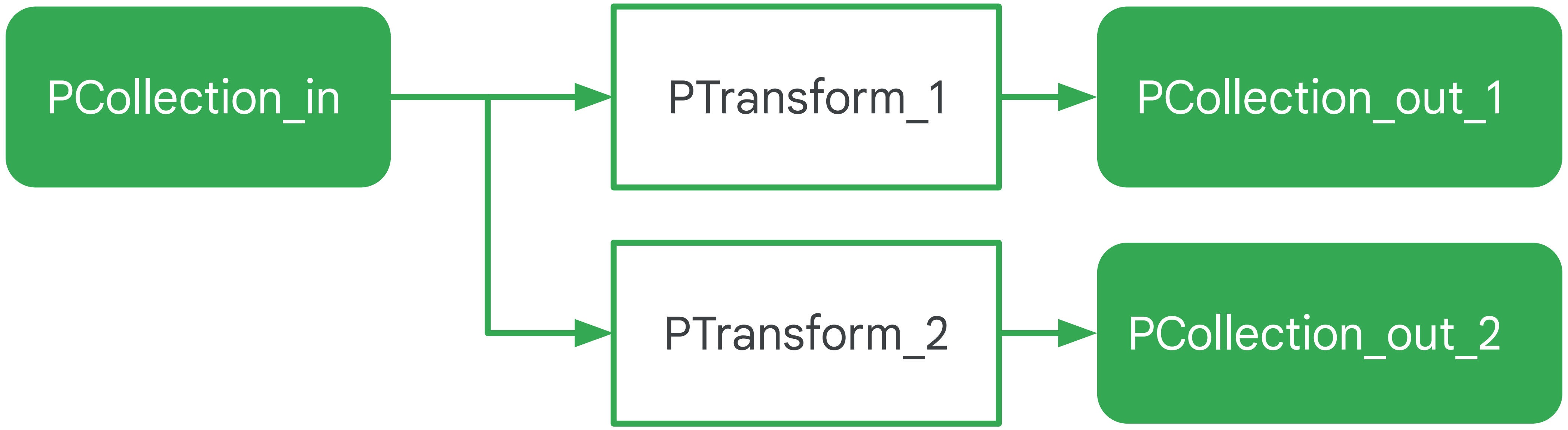
```
PCollection_out = (PCollection_in | PTransform_1
                   | PTransform_2
                   | PTransform_3)
```

Java

Java uses the **.apply** method

```
PCollection_out = PCollection_in.apply(PTransform_1)
.apply(PTransform_2)
.apply(PTransform_3)
```

How to construct a branching pipeline



Python

```
PCollection_out_1 = PCollection_in | PTransform_1
PCollection_out_2 = PCollection_in | PTransform_2
```

Java

```
PCollection_out_1 = PCollection_in.apply(PTransform_1)
PCollection_out_2 = PCollection_in.apply(PTransform_2)
```

A pipeline is a directed graph of steps

Python

```
import apache_beam as beam

if __name__ == '__main__':

    with beam.Pipeline(argv=sys.argv) as p:

        (p
            | beam.io.ReadFromText('gs://...')
            | beam.FlatMap(count_words)
            | beam.io.WriteToText('gs://...')
        )

    # end of with-clause: runs, stops the pipeline
```

Create a pipeline parameterized by command line flags

Read input

Apply transform

Write output

Run a pipeline on Dataflow

Python

```
import apache_beam as beam

options = {'project': <project>,
           'runner': 'DataflowRunner',
           'region': <region>,
           'setup_file': <setup.py file>}
pipeline_options = beam.pipeline.PipelineOptions(flags=[],
**options)
pipeline = beam.Pipeline(options = pipeline_options)
```

Where to run

This creates the pipeline

Pipeline Execution using DataflowRunner

Run local

```
python ./grep.py
```

Run on cloud

```
python ./grep.py \
      --project=$PROJECT \
      --job_name=myjob \
      --staging_location=gs://$BUCKET/staging/ \
      --temp_location=gs://$BUCKET/tmp/ \
      --runner=DataflowRunner
```

Read data from local file system, Cloud Storage, Pub/Sub, BigQuery, ...

```
with beam.Pipeline(options=pipeline_options) as p:
```

Read from Cloud Storage (returns a string)

```
lines = p | beam.io.ReadFromText("gs://.../input-*.csv.gz")
```

Read from Pub/Sub (returns a string)

```
lines = p | beam.io.ReadStringsFromPubSub(topic=known_args.input_topic)
```

Read from BigQuery (returns rows)

```
query = "SELECT x, y, z FROM `project.dataset.tablename`"
BQ_source = beam.io.BigQuerySource(query = <query>, use_standard_sql=True)
BQ_data = pipeline | beam.io.Read(BQ_source)
```

Setup

Read

Write to a BigQuery table

Establish reference to BigQuery table

```
from apache_beam.io.gcp.internal.clients import bigquery

table_spec = bigquery.TableReference(
    projectId='clouddataflow-readonly',
    datasetId='samples',
    tableId='weather_stations')
```

Write to BigQuery table

```
p | beam.io.WriteToBigQuery(
    table_spec,
    schema=table_schema,
    write_disposition=beam.io.BigQueryDisposition.WRITE_TRUNCATE,
    create_disposition=beam.io.BigQueryDisposition.CREATE_IF_NEEDED)
```

Create a PCollection from in-memory data

Python

```
city_zip_list = [
    ('Lexington', '40513'),
    ('Nashville', '37027'),
    ('Lexington', '40502'),
    ('Seattle', '98125'),
    ('Mountain View', '94041'),
    ('Seattle', '98133'),
    ('Lexington', '40591'),
    ('Mountain View', '94085'),
]
citycodes = p | 'CreateCityCodes' >> beam.Create(city_zip_list)
```

This is the display name of the pipeline step

PCollection

Map and FlatMap

Use Map for 1:1 relationship between input and output

```
'WordLengths' >> beam.Map(word, len(word))
```

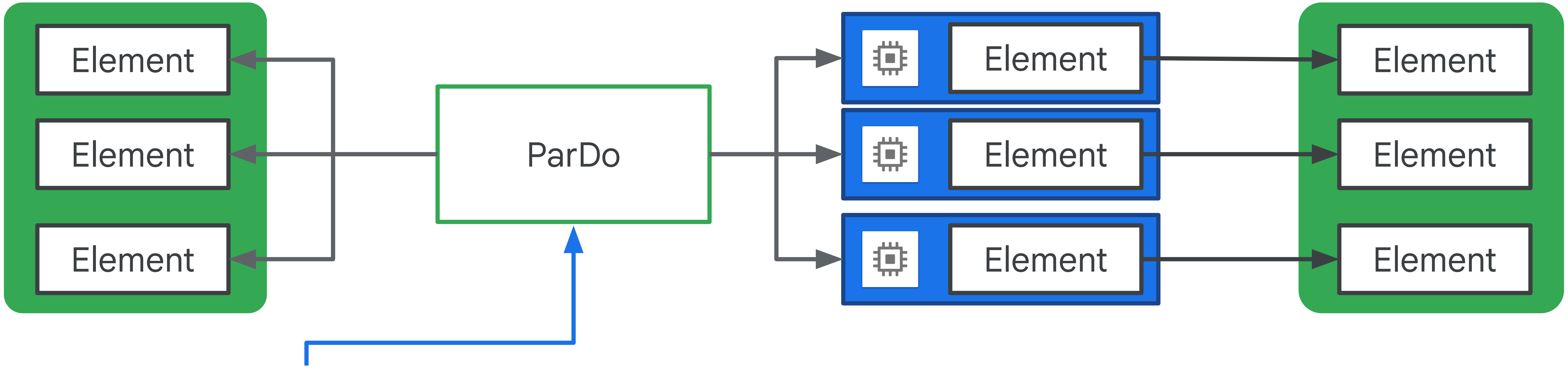
Map (fn) uses a callable fn to do a one-to-one transformation.

Use FlatMap for non 1:1 relationships, usually with a generator

```
def my_grep(line, term):
   if term in line:
      yield line  <---------------------Generator

'Grep' >> beam.FlatMap(my_grep(line, searchTerm))
```

FlatMap is similar to Map, but fn returns an iterable of zero or more elements.
The iterables are flattened into one PCollection.

ParDo implements parallel processing



- ParDo acts on one item at a time in the PCollection
- Multiple instances of class on many machines
- Should not contain any state

Uses:

- Filtering a data set, choosing which elements to output.
- Formatting or type-converting each element in a dataset.
- Extracting parts of each element in a dataset.
- Performing computations on each element in a dataset.

ParDo requires code passed as a DoFn object

Python

```
words = ...

class ComputeWordLengthFn(beam.DoFn):     DoFN
  def process(self, element):
    return [len(element)]                 ParDo

word_lengths = words | beam.ParDo(ComputeWordLengthFn())
```

Apply a ParDo to the PCollection "words" to compute lengths for each word.

The **input** is a PCollection of strings.

The DoFn to perform on each element in the input PCollection.

The **output** is a PCollection of integers.

ParDo method can emit multiple variables

```
results = (words | beam.ParDo(ProcessWords(),
   cutoff_length=2, marker='x')
   .with_outputs('above_cutoff_lengths', 'marked strings', main='below_cutoff_strings'))

below  = results.below_cutoff_strings
above  = results.above_cutoff_lengths
marked = results['marked strings']
```

Lab Intro

Serverless Data Analysis with Dataflow: A Simple Dataflow Pipeline (Python/Java)

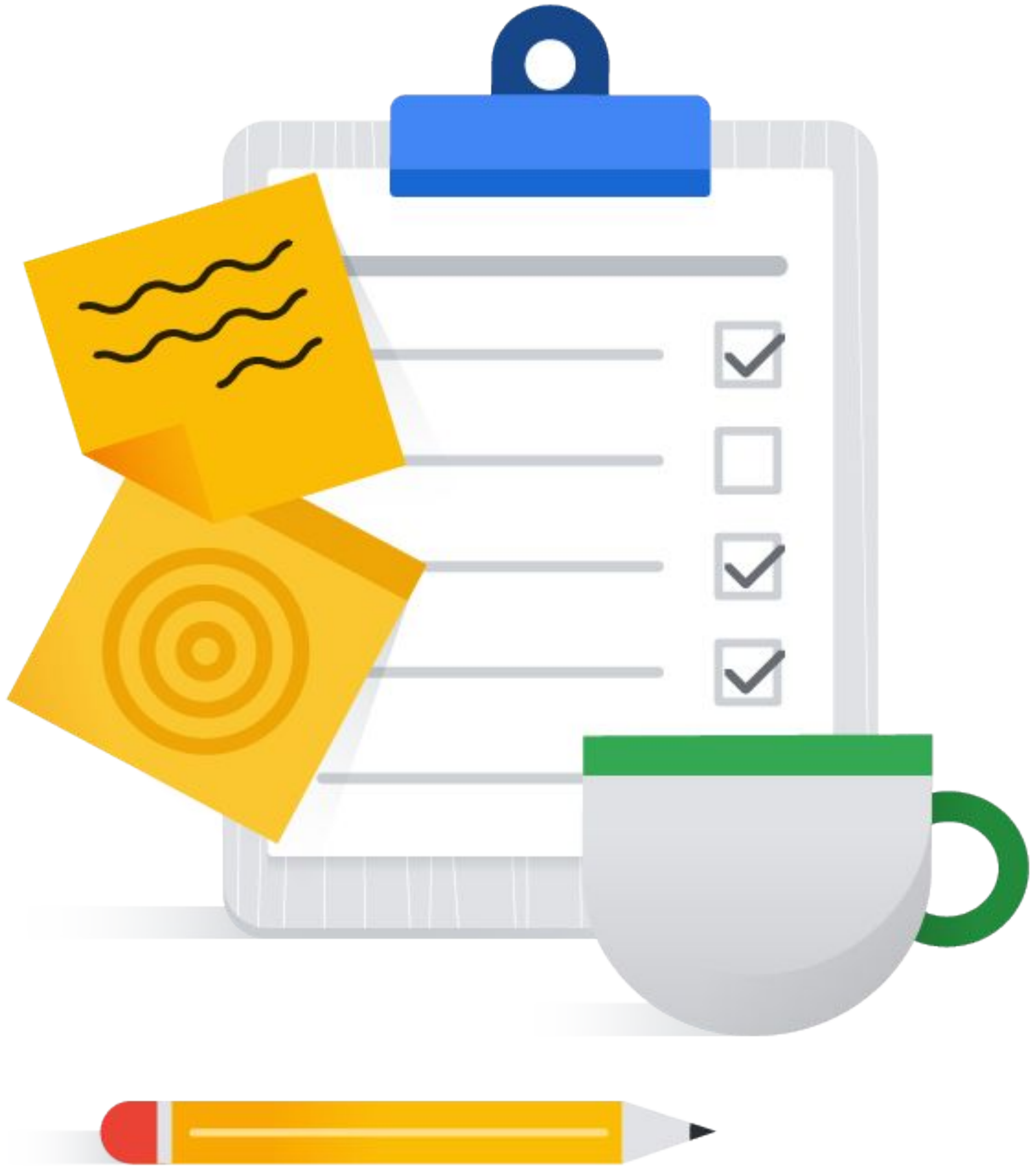
Lab objectives

01 Open Dataflow project

02 Pipeline filtering

03 Execute the pipeline locally and on the cloud

Serverless Data Processing with Dataflow



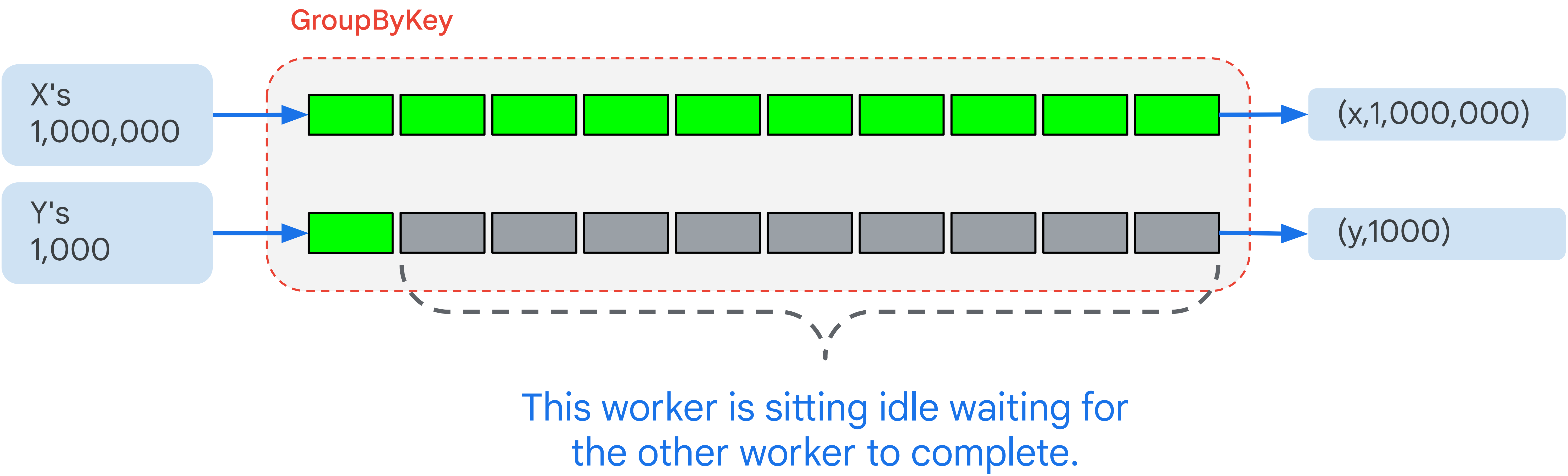
GroupByKey explicitly shuffles key-values pairs

```
cityAndZipcodes = p | beam.Map(fields[0], fields[1])

grouped = cityAndZipCodes | beam.GroupByKey()
```

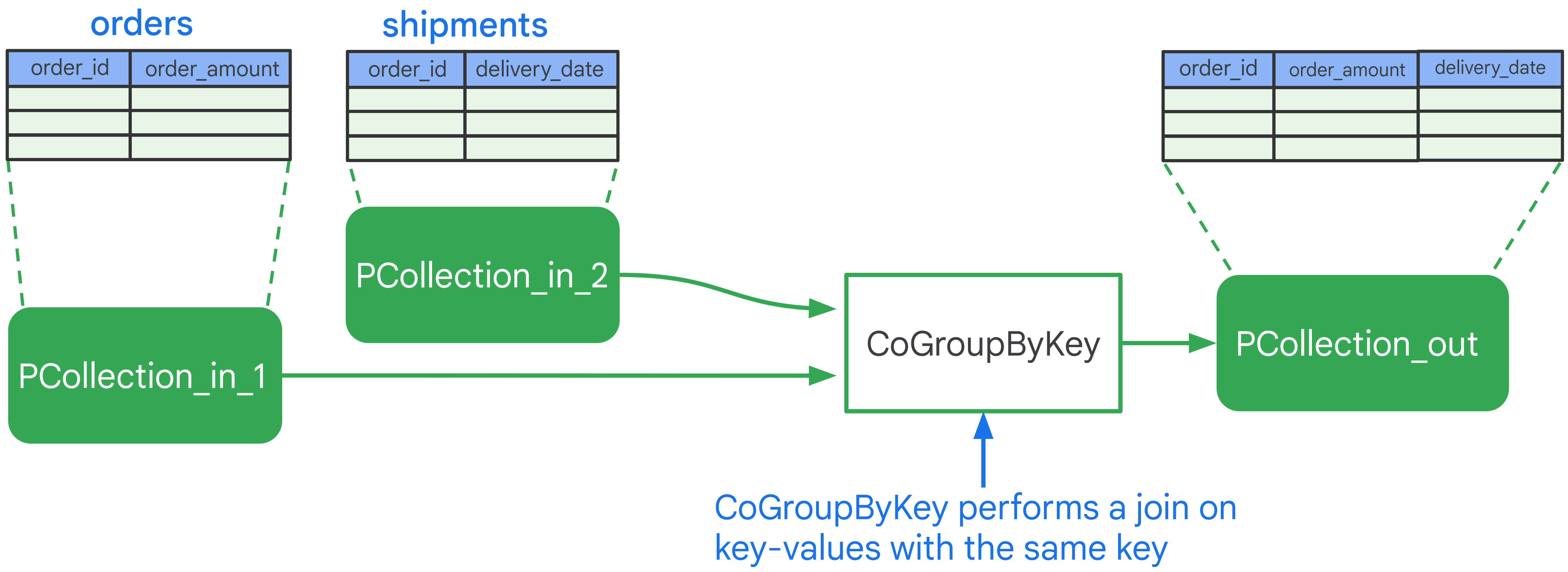
```
Lexington, 40513
Nashville, 37027
Lexington, 40502
Seattle, 98125
Mountain View, 94041
Seattle, 98133
Lexington, 40591
Mountain View, 94085
```

```
Lexington, [40513, 40502, 40592]
Nashville, [37027]
Seattle, [98125, 98133]
Mountain View, [94041, 94085]
```

Data skew makes grouping less efficient at scale



CoGroupByKey joins two or more key-value pairs




```
results = ({'orders': orders, 'shipments': shipments}
           | beam.CoGroupByKey())
```

Combine (reduce) a PCollection

Applied to a PCollection of values

```
totalAmount = salesAmounts | CombineGlobally(sum)
```

Applied to a grouped Key-Value pair

```
totalSalesPerPerson = salesRecords | CombinePerKey(sum)
```

Each element of salesRecords is a tuple: (salesPerson, salesAmount)

Pre-built combine functions for many common numeric combination operations such as sum, mean, min, and max

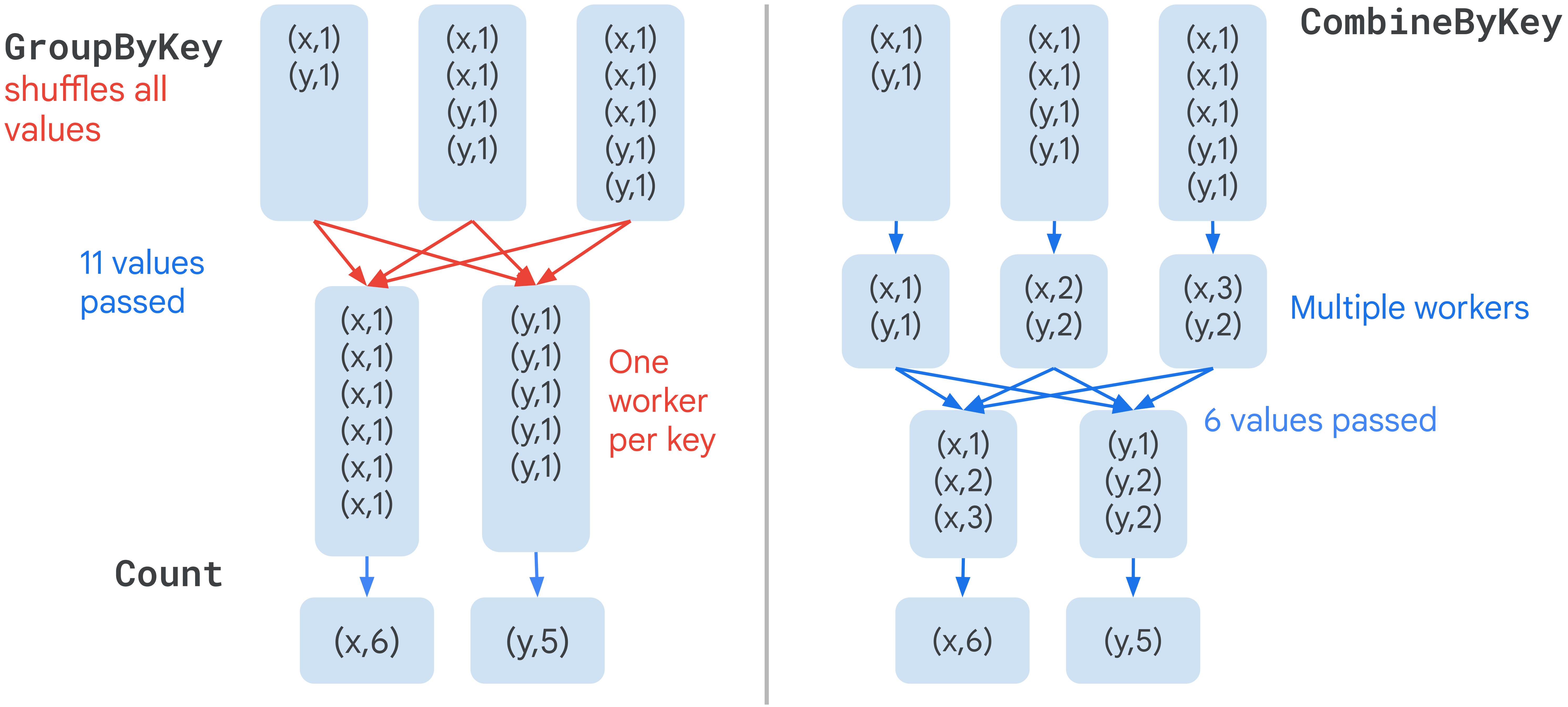
CombineFn works by overriding existing operations

You must provide four operations by overriding the corresponding methods

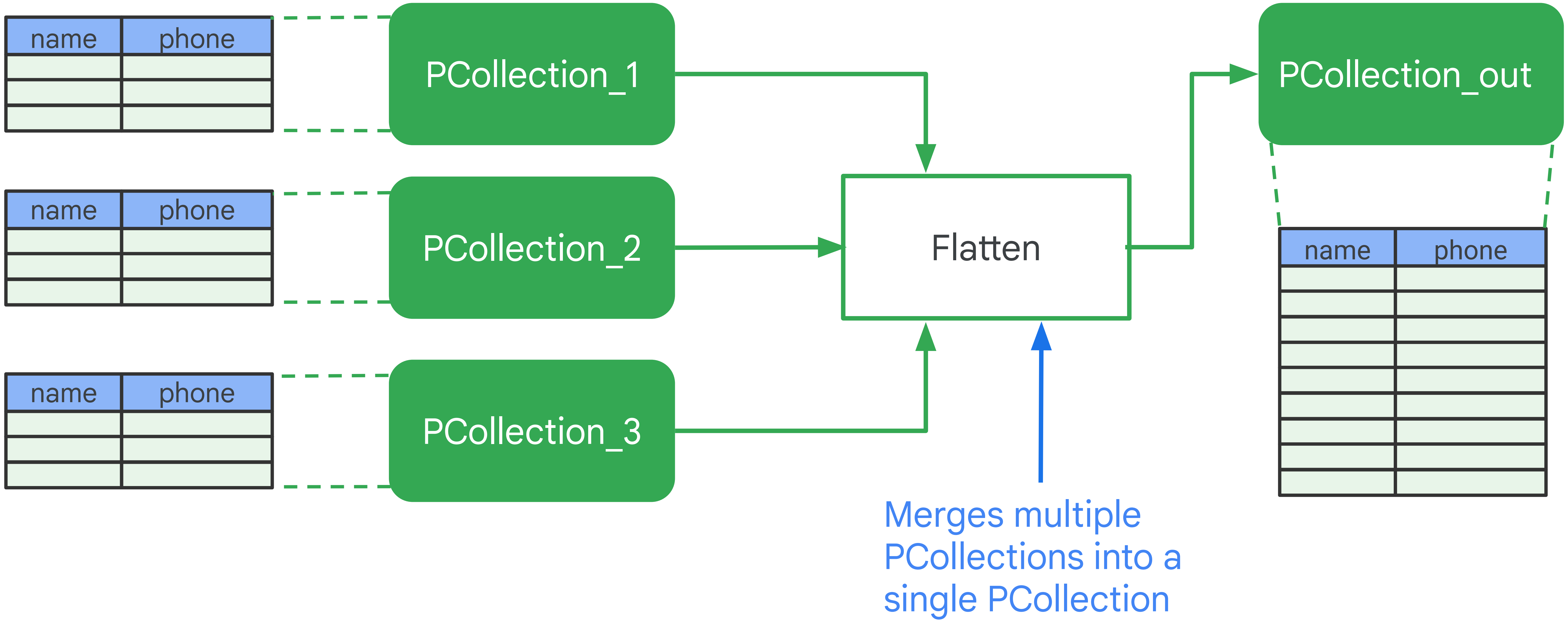
```
class AverageFn(beam.CombineFn):

  def create_accumulator(self):
    return (0.0, 0)

  def add_input(self, sum_count, input):
    (sum, count) = sum_count
    return sum + input, count + 1

  def merge_accumulators(self, accumulators):
    sums, counts = zip(*accumulators)
    return sum(sums), sum(counts)

  def extract_output(self, sum_count):
    (sum, count) = sum_count
    return sum / count if count else float('NaN')
```

```
pc = ...
average = pc | beam.CombineGlobally(AverageFn())
```

Combine is more efficient than **GroupByKey**

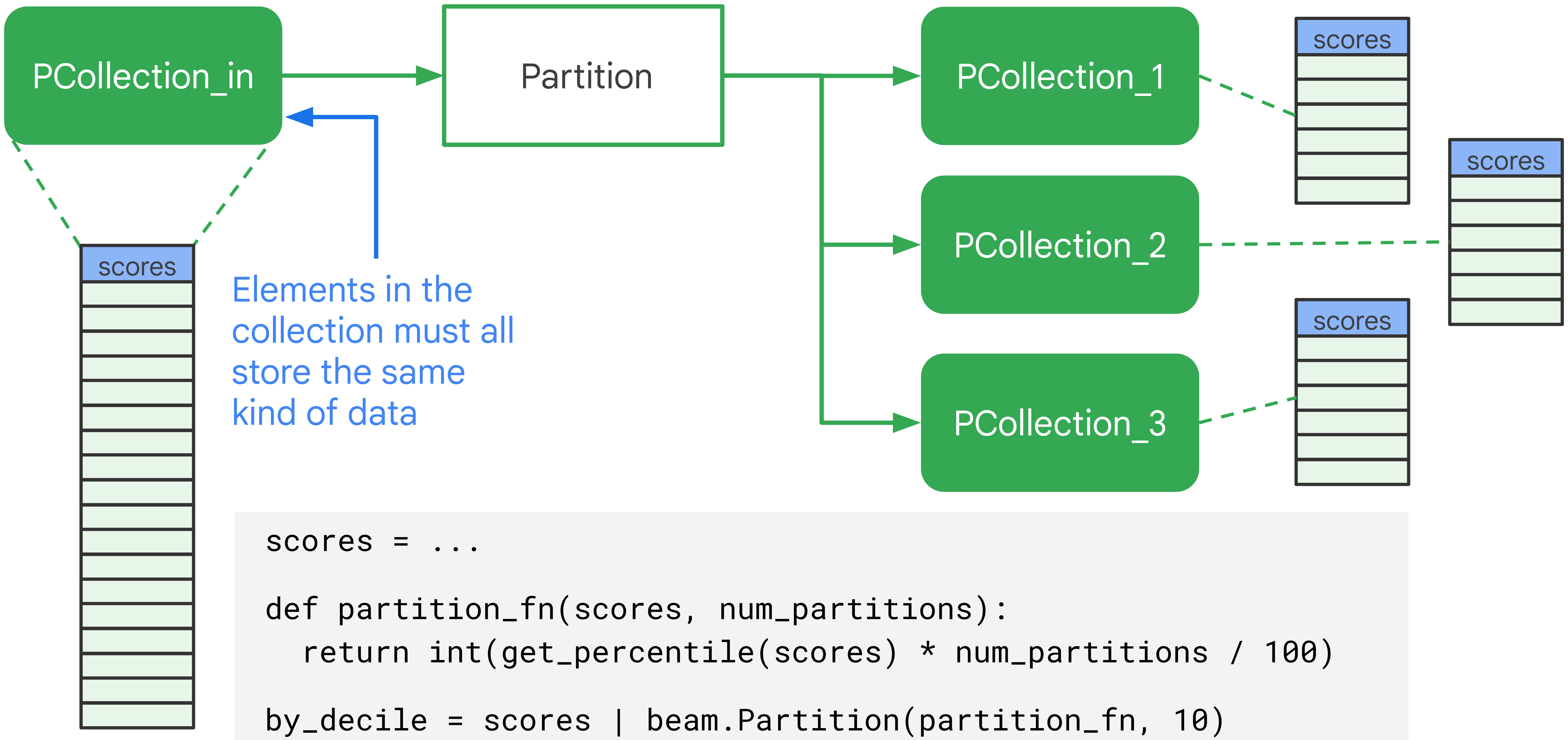


Flatten merges identical PCollections




```
merged = ((pcoll1, pcoll2, pcoll3) | beam.Flatten())
```

Partition splits PCollections into smaller PCollections




```
scores = ...

def partition_fn(scores, num_partitions):
  return int(get_percentile(scores) * num_partitions / 100)

by_decile = scores | beam.Partition(partition_fn, 10)
```

Lab Intro

Serverless Data Analysis with Dataflow: MapReduce in Dataflow (Python/Java)

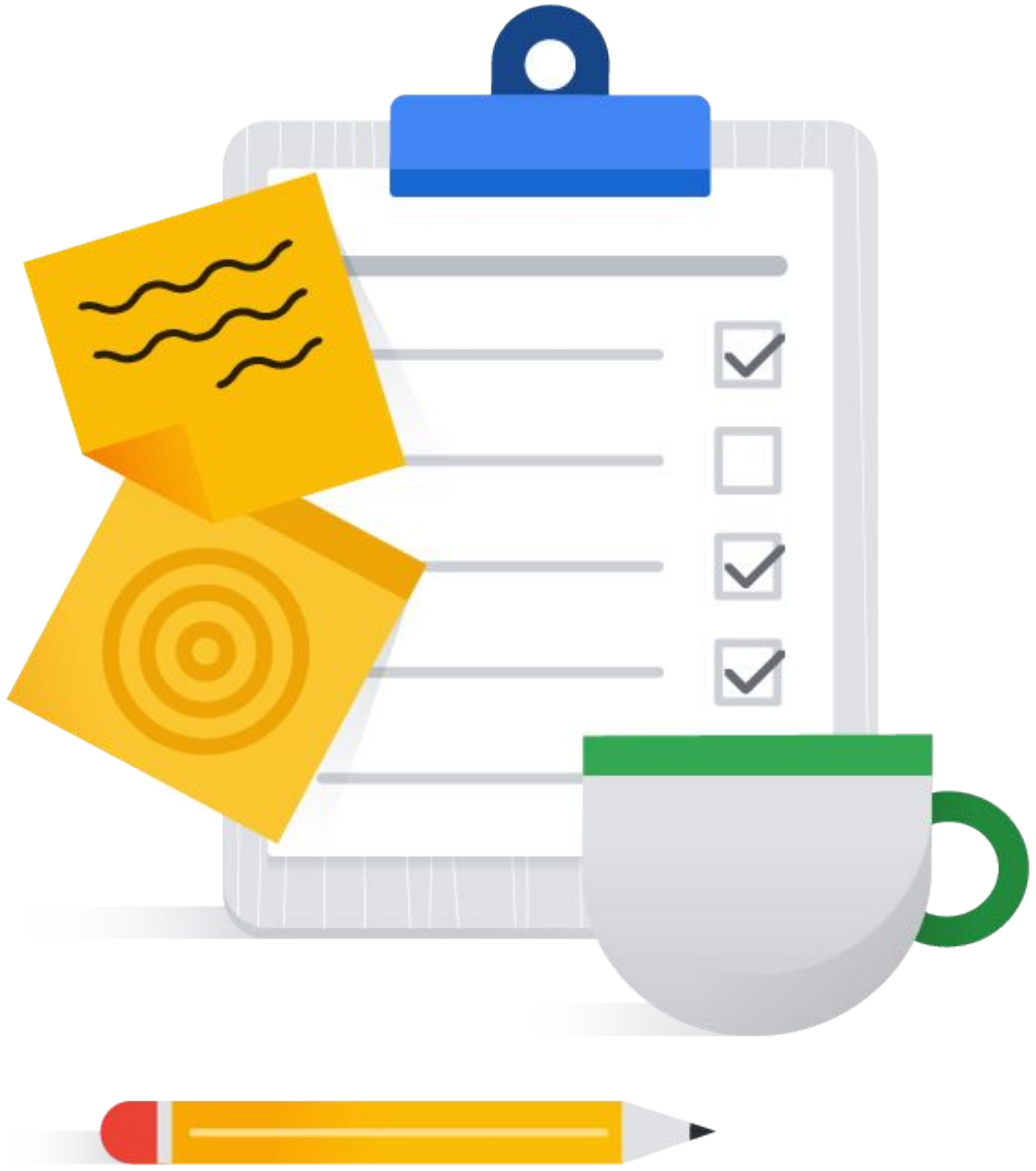
Lab objectives

01 Identify Map and Reduce operations

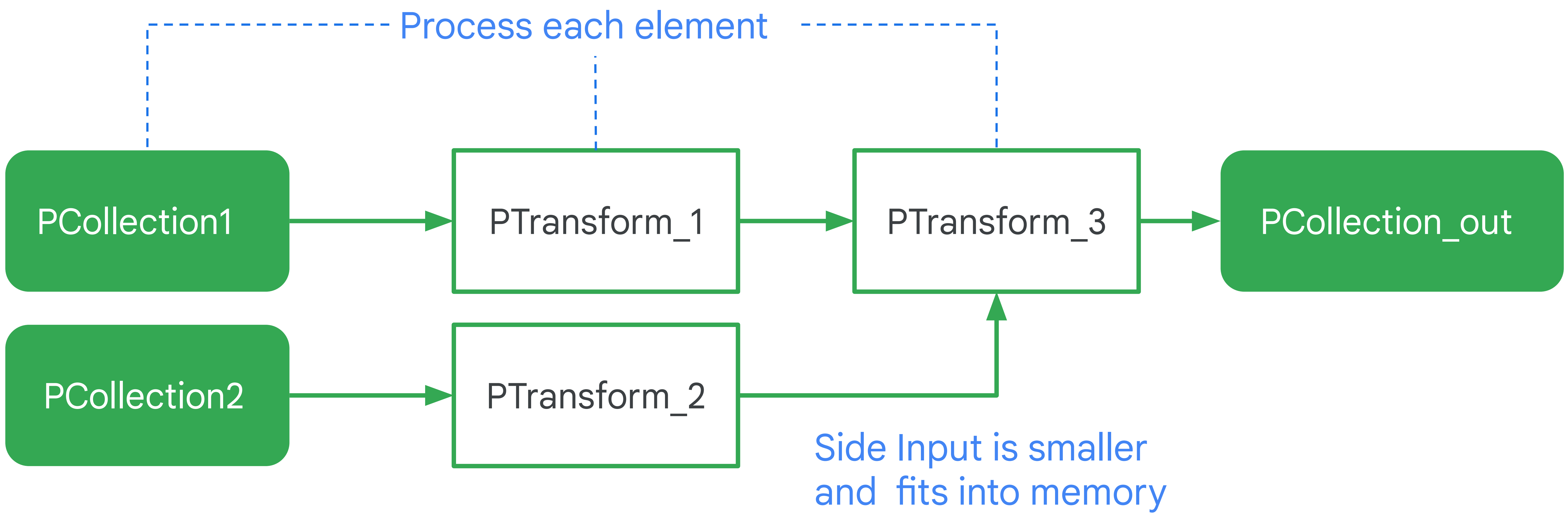
02 Execute the pipeline

03 Use command line parameters

Serverless Data Processing with Dataflow



Use side inputs to inject additional runtime data



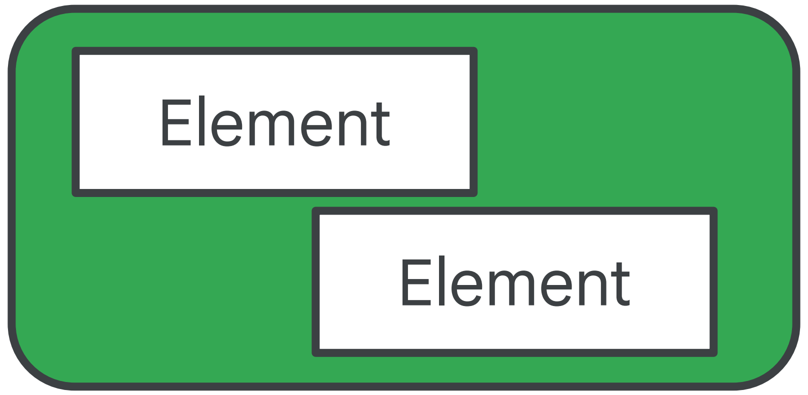
How side inputs work

```
words = …

def filter_using_length(word, lower_bound, upper_bound=float('inf')):
  if lower_bound <= len(word) <= upper_bound:
    yield word

small_words = words | 'small' >> beam.FlatMap(filter_using_length, 0, 3)

avg_word_len = (words
                | beam.Map(len)
                | beam.CombineGlobally(beam.combiners.MeanCombineFn()))

larger_than_average = (words | 'large' >> beam.FlatMap(
    filter_using_length,
    lower_bound=pvalue.AsSingleton(avg_word_len)))
```

Side input

Every PCollection is processed within a Window

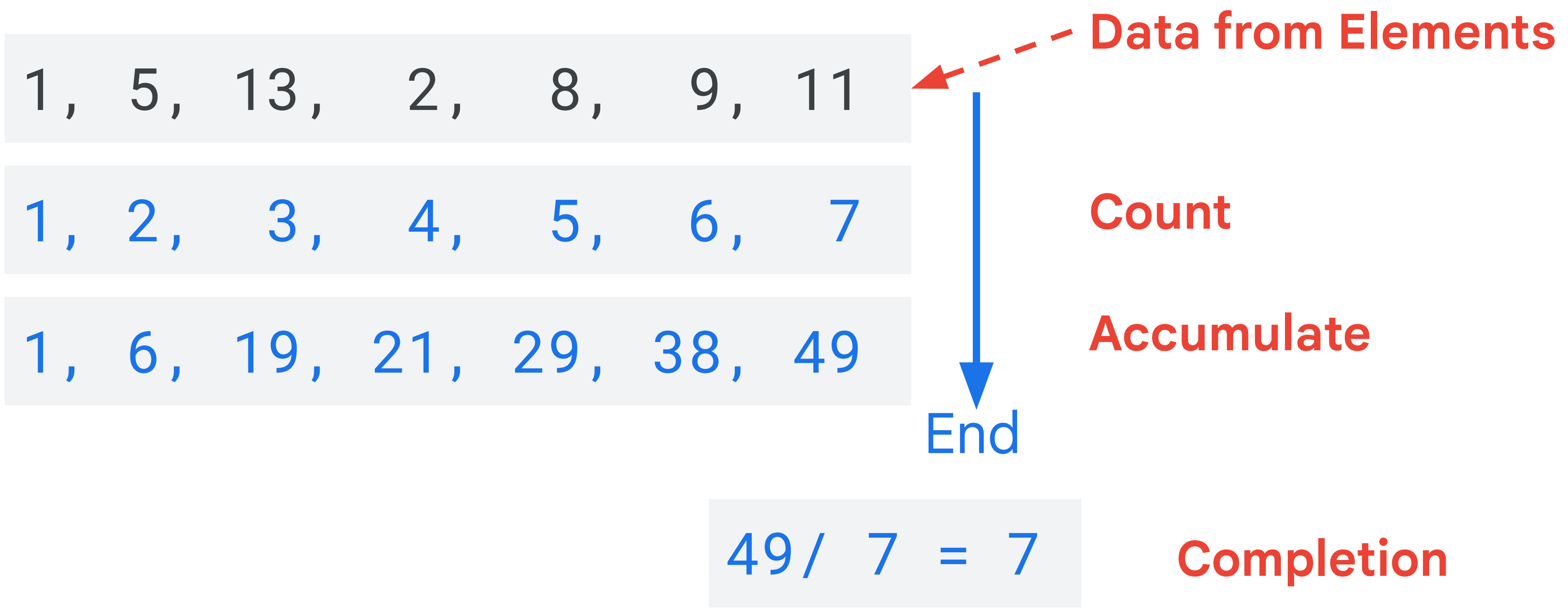
Bounded PCollection



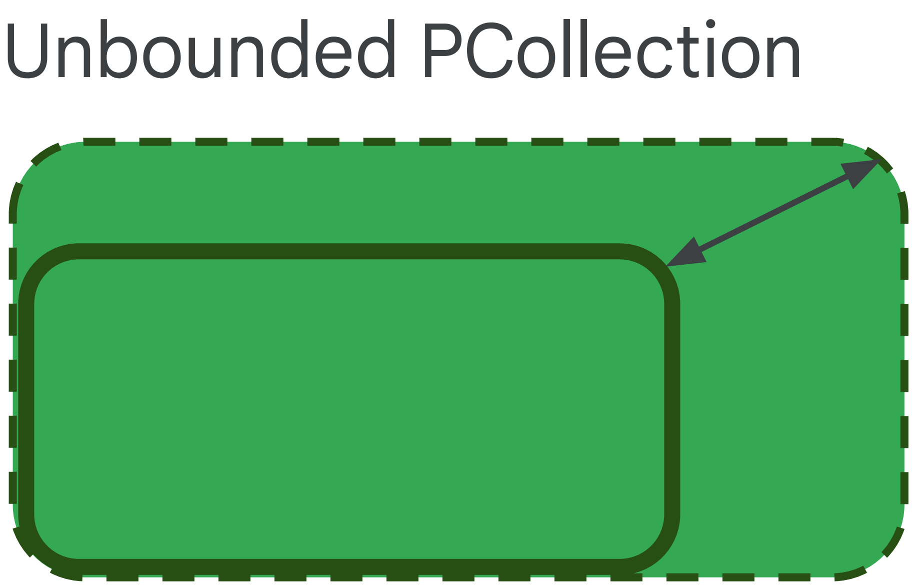
1 The default window is called the global window, it starts when the data is input and ends when the last element in the collection is processed.

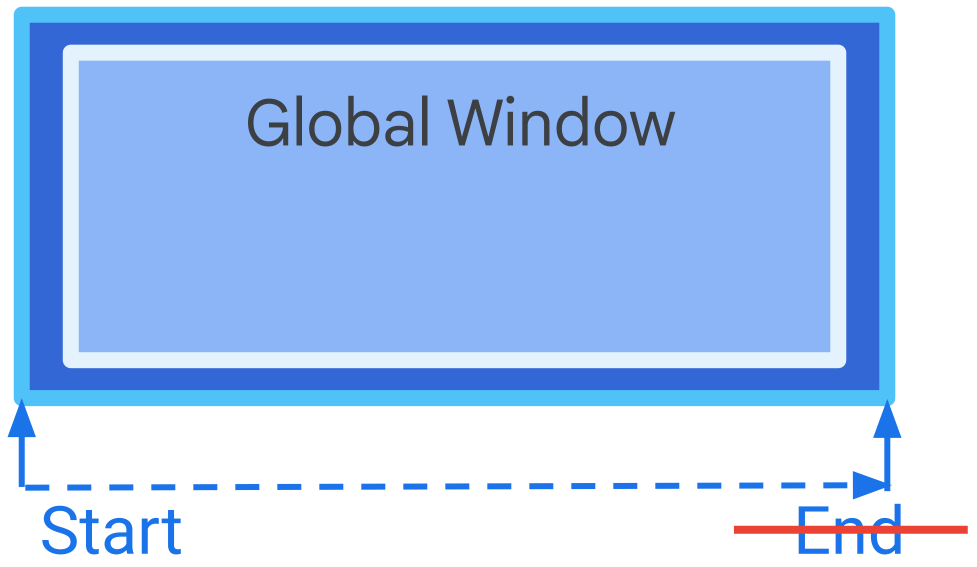
2 In Bounded PCollections, commonly the Elements are all marked as occurring at the same time. (Example: TextIO does this.) So the global window basically ignores the timing information.

3



The global window is not very useful for an unbounded PCollection





1. The timing associated with the elements in an Unbounded PCollection is usually important to processing the data.

2. An Unbounded PCollection has no defined end or last element. So it can never perform the completion step.

   This is particularly important for **GroupByKey** and **Combine**, which perform the shuffle after 'end'.

3. The discussion about Unbounded PCollections and Windows will be continued in *Building Resilient Streaming Analytics Systems on Google Cloud*.

Setting a single global window for a PCollection

Single global window

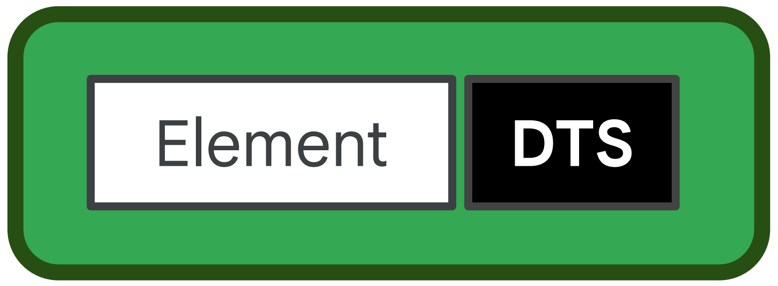
Python

```
from apache_beam import window
session_windowed_items = (
    items | 'window' >> beam.WindowInto(window.GlobalWindows()))
```

This is the default.

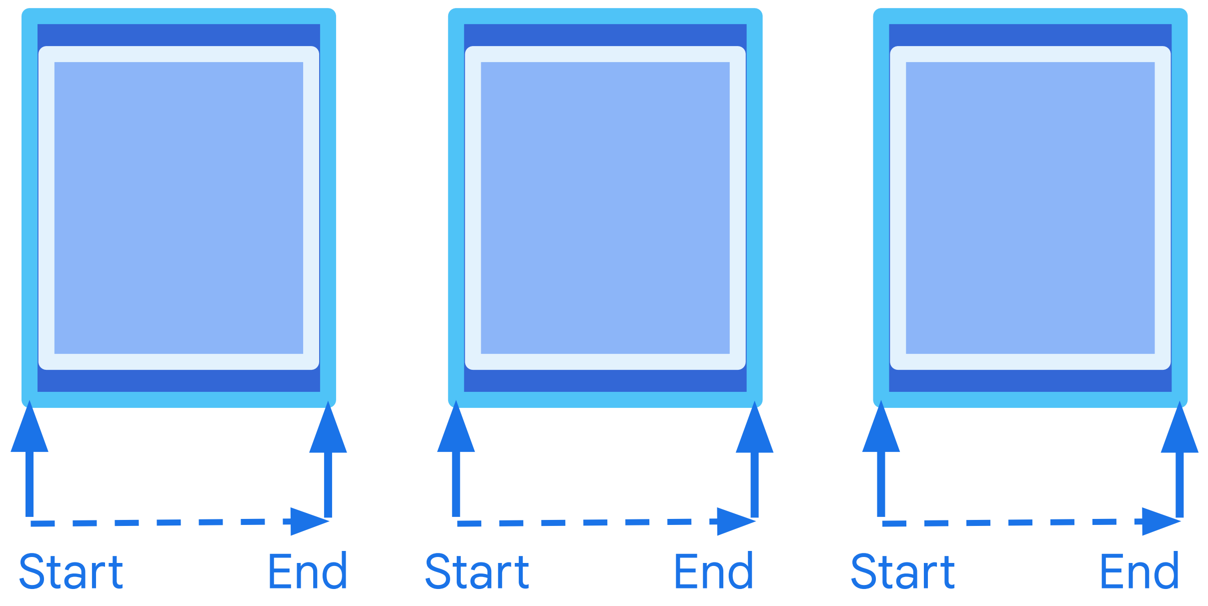
This code illustrates how you could explicitly set it.

Time-based Windows can be useful for processing time-series data



1

You may have to prepare the date-timestamp.
In this example, the dts of the data (log writing time) becomes the element time. Now the elements have different times from one another.



2

Using time based windowing the data is processed in groups.

In the example, each group gets its own average.

3

There are different kinds of windowing.

Shown is "Fixed" There is also "Sliding" and "Session".

Using Windowing with Batch (group by time)

Python

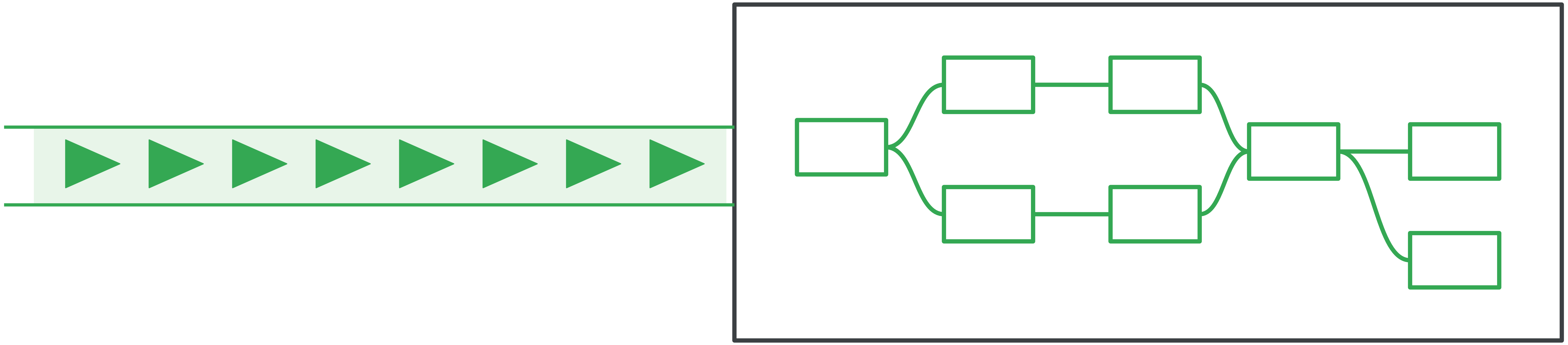
```
lines = p | 'Create' >> beam.io.ReadFromText('access.log')
windowed_counts = (
    lines
    | 'Timestamp' >> beam.Map(beam.window.TimestampedValue(x, extract_timestamp(x)))
    | 'Window' >> beam.WindowInto(beam.window.SlidingWindows(60, 30))
    | 'Count' >>
(beam.CombineGlobally(beam.combiners.CountCombineFn()).without_defaults())
)
windowed_counts =  windowed_counts | beam.ParDo(PrintWindowFn())
```

access.log (example)

```
131.108.5.17 - - [29/Apr/2019:04:53:15 -0800] "GET /view HTTP/1.1" 200 7352
131.108.5.17 - - [29/Apr/2019:05:21:35 -0800] "GET /view HTTP/1.1" 200 5253
```

Date Time Stamp

Streaming data processing with Dataflow



Discussion of streaming continues in **Building Resilient Streaming Analytics Systems on Google Cloud.**

Lab Intro

Serverless Data Analysis with Dataflow: Side Inputs (Python/Java)

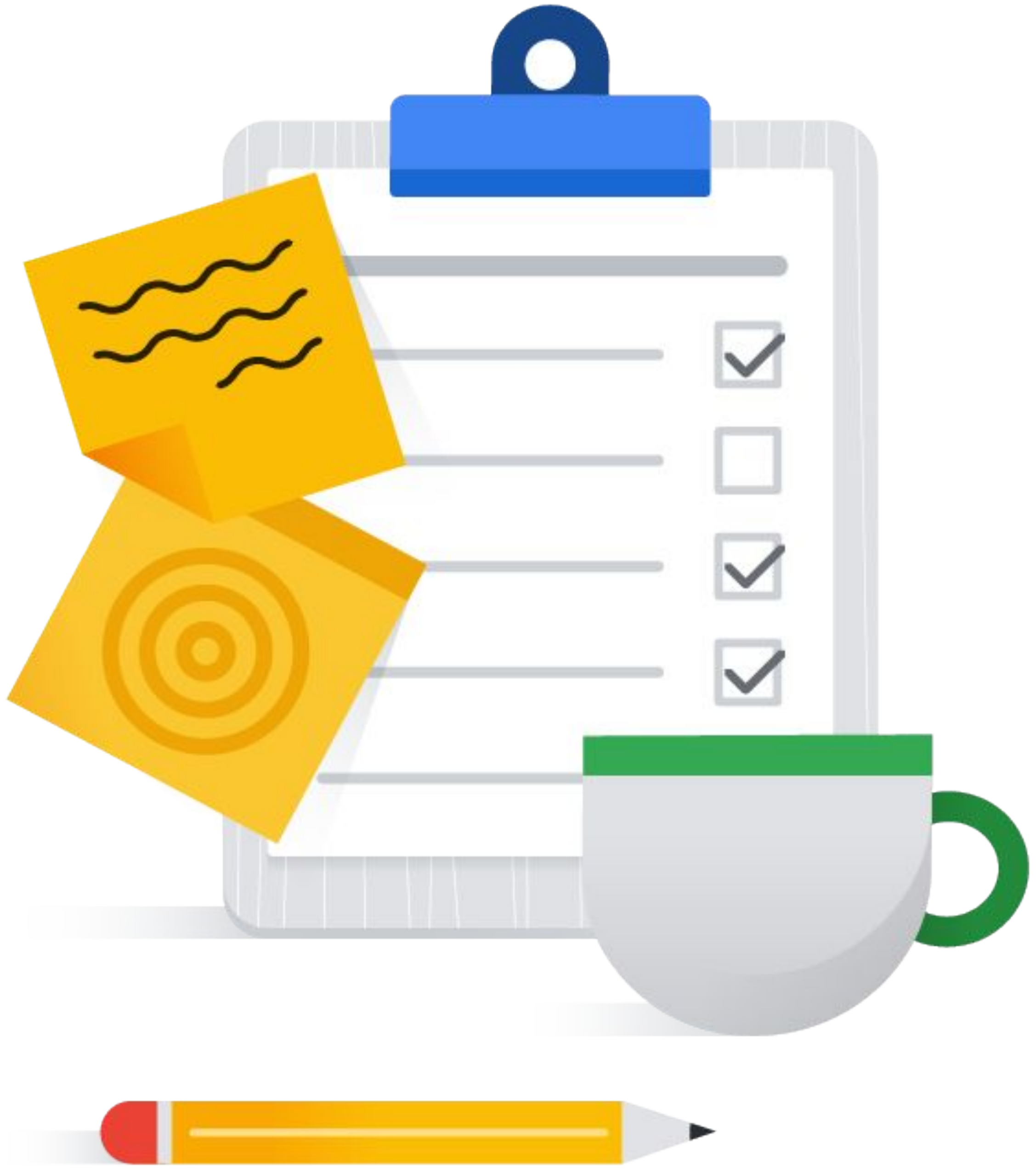
Lab objectives

01 Try out a BigQuery query

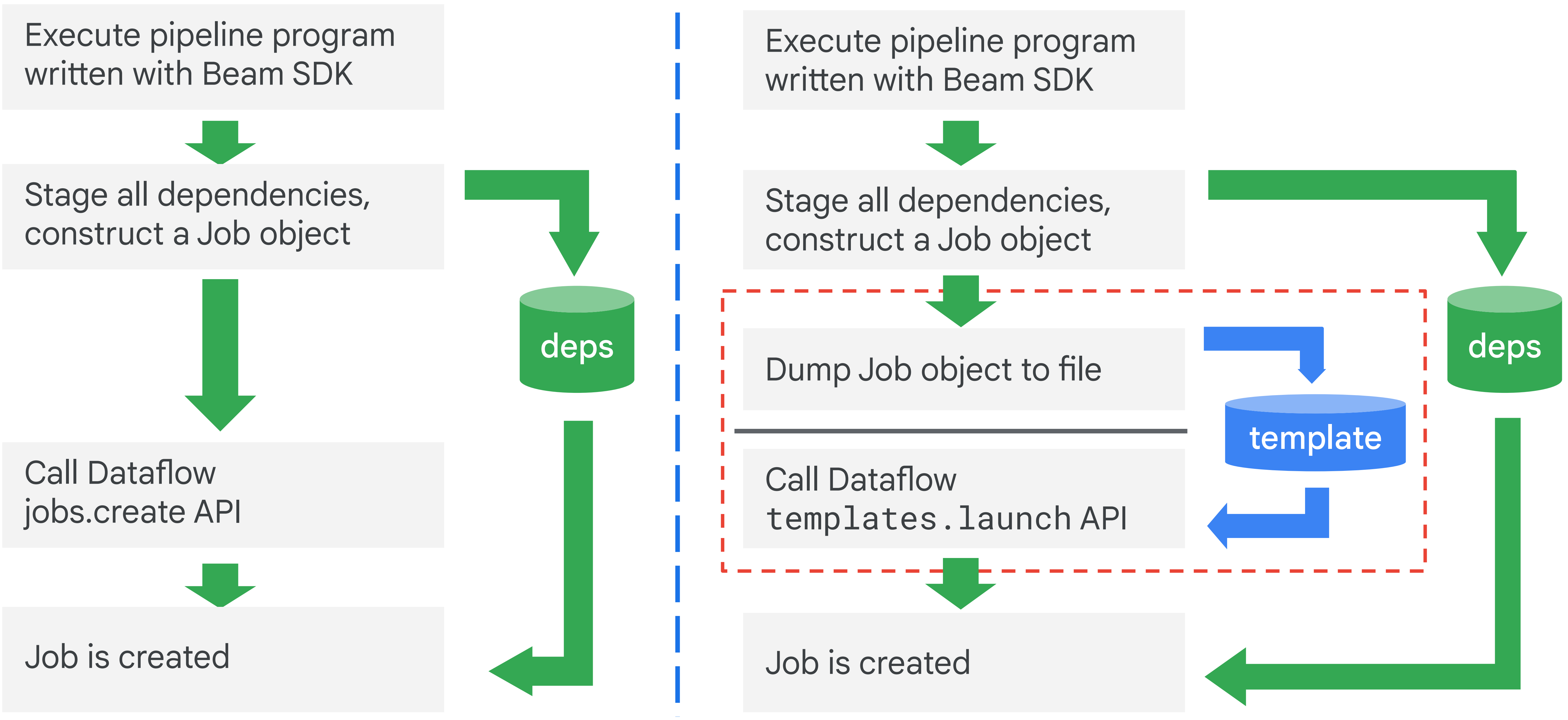
02 Explore the pipeline code

03 Execute the pipeline

Serverless Data Processing with Dataflow



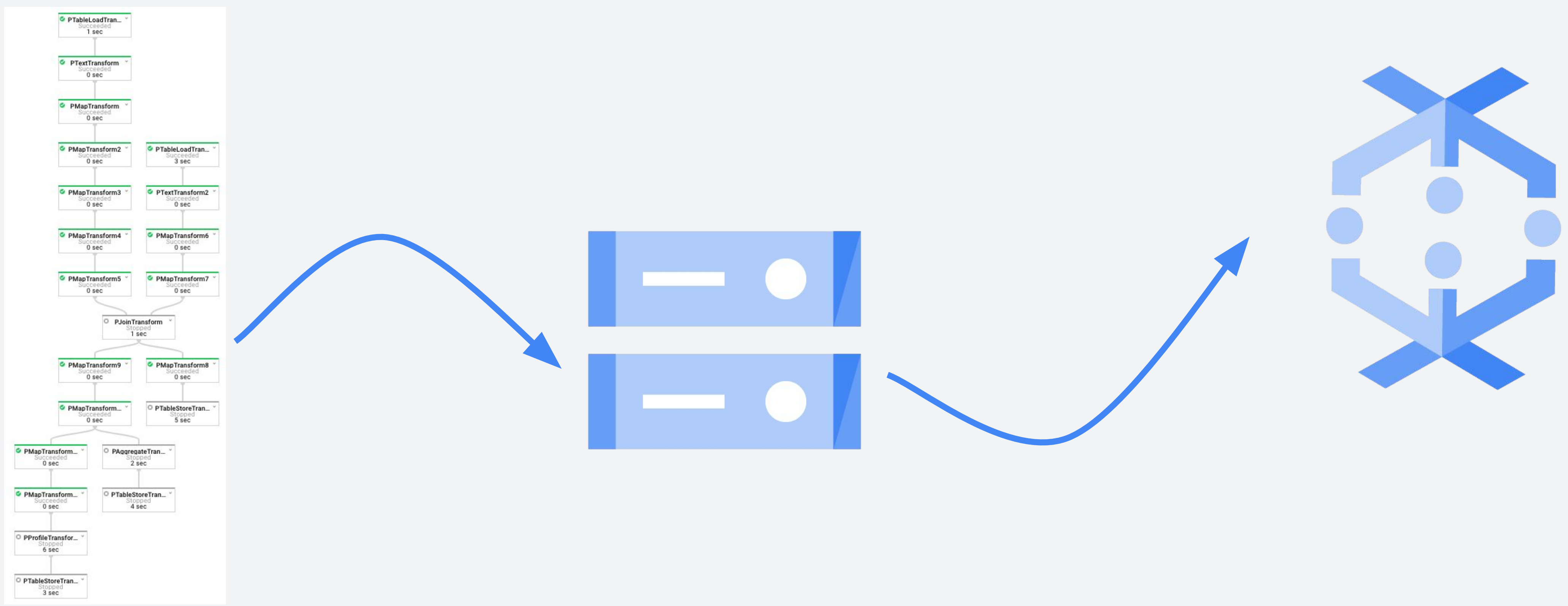
Dataflow templates enable the rapid deployment of standard job types



Traditional workflow all happens in one environment

Development environment

Dataflow SDK
Java
Python



Developer executes pipeline on Dataflow

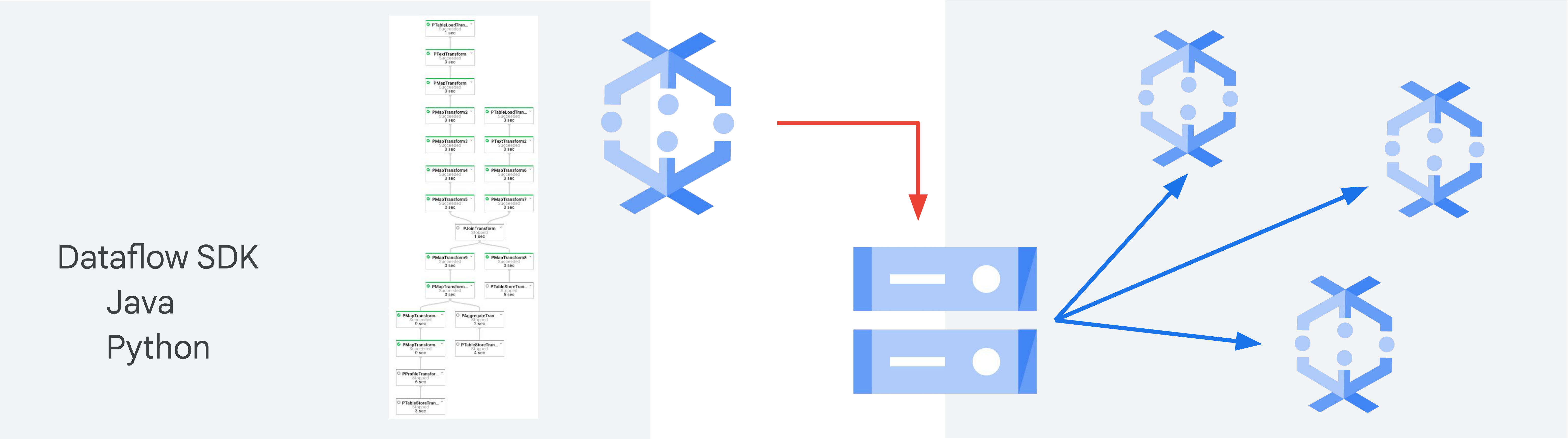
SDK stages files in Cloud Storage

Developer or user submits source code to run Dataflow jobs

Template workflow supports non-developer users

Development environment

Production environment



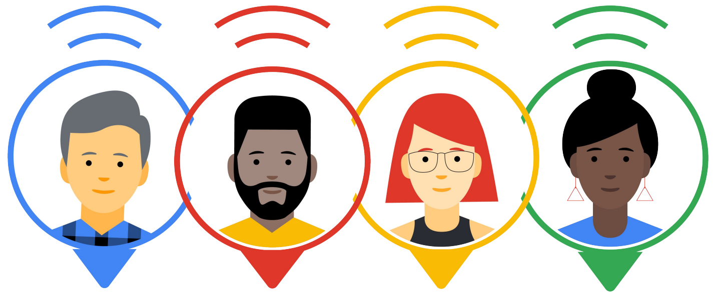
Developer creates pipeline in the development environment

Dataflow stores template in Cloud Storage

Users submit templates to run jobs

Get started with Google-provided templates

Pre-written Dataflow pipelines for common data tasks that can be triggered with a single command or UI form.



Target users

- App developers
- DB admins
- Analysts
- Data scientists
- Data engineers

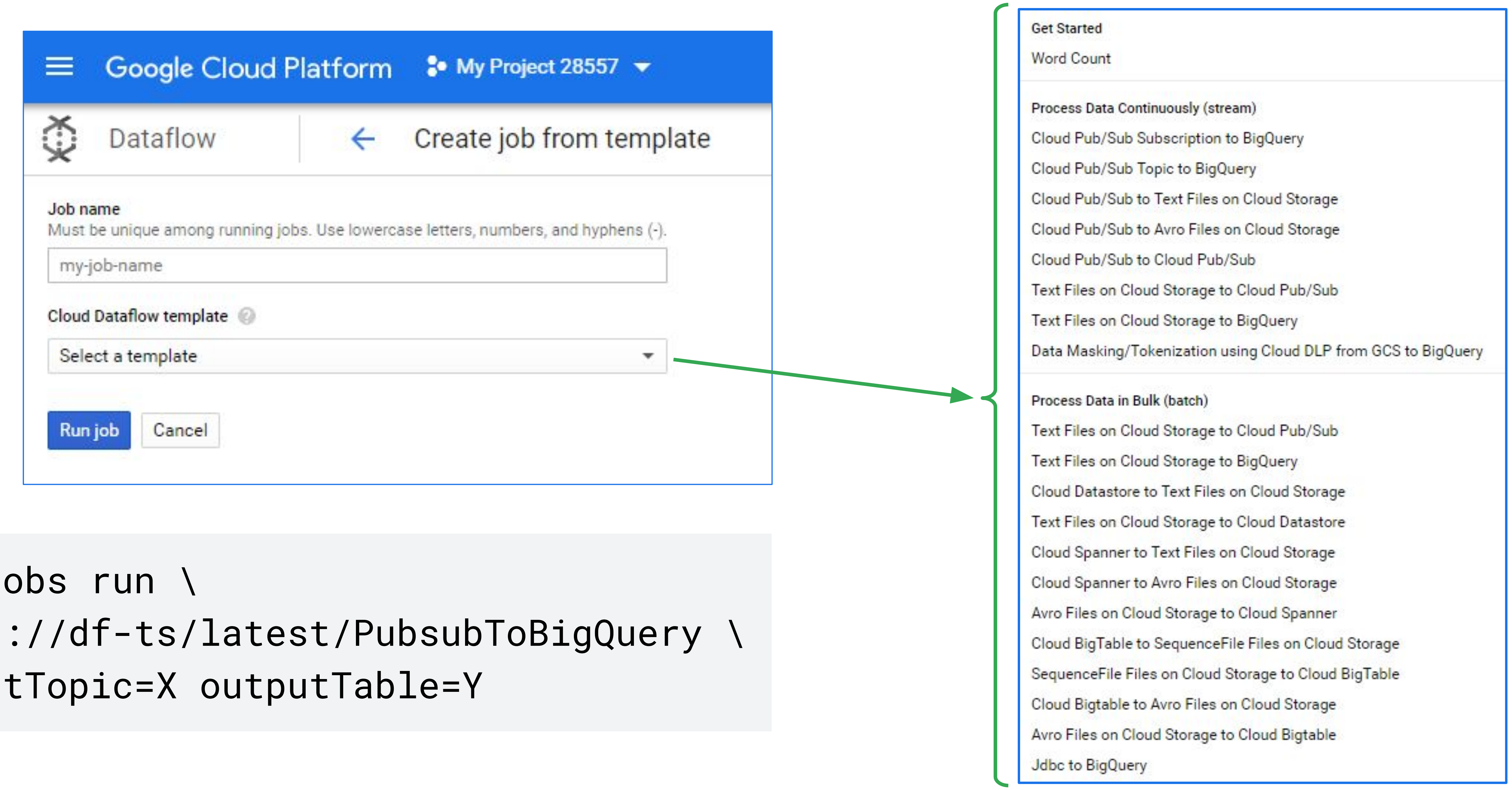
Exposure

- Through Google-provided Dataflow templates
- Embedded in other Google Cloud products calling templates API

Data Fusion

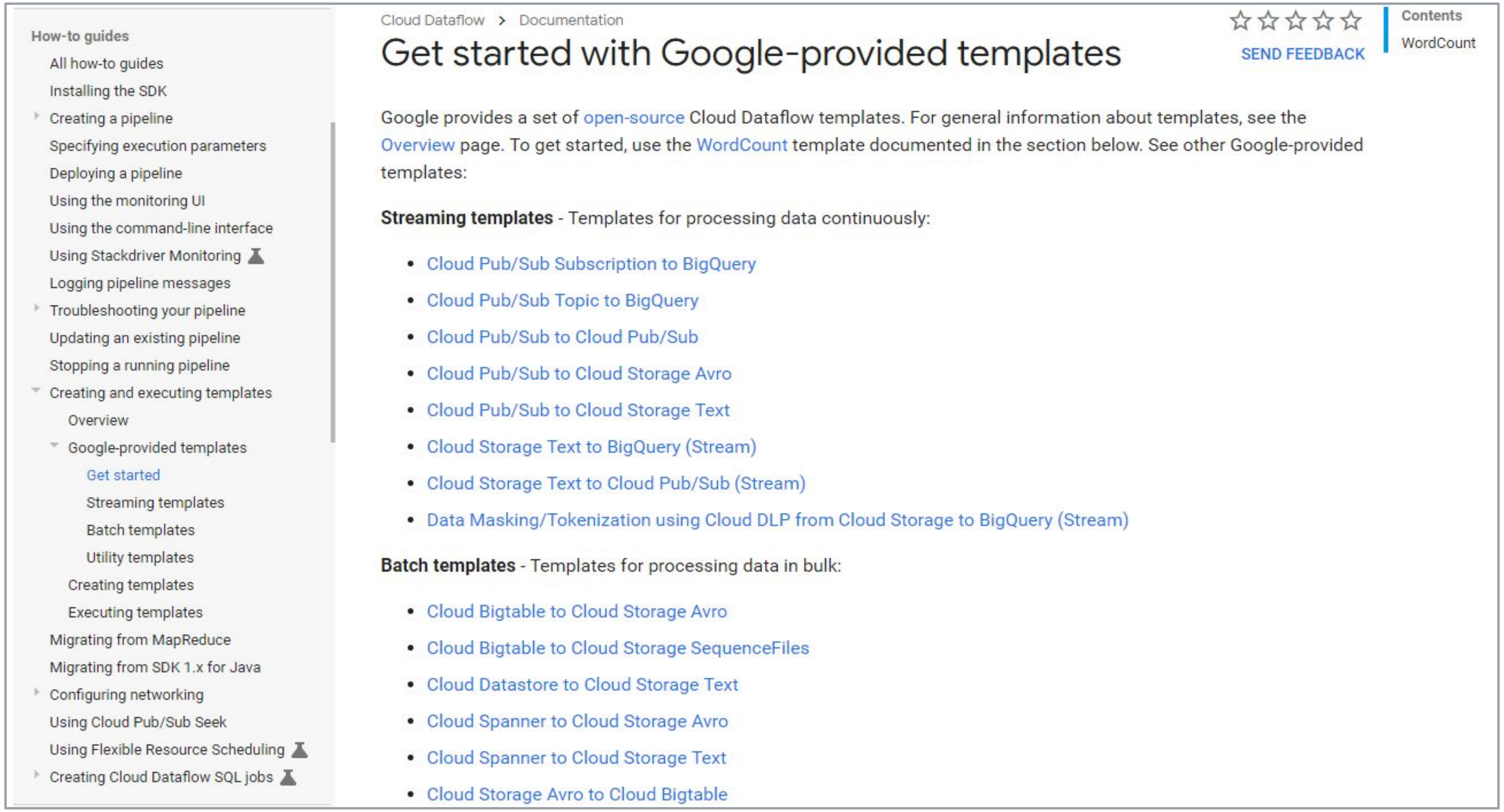
- Branded Google product
- UI pipeline builder
- Scheduler/orchestrator

Execute templates with the Cloud Console, `gcloud` command-line tool, or the REST API




```
gcloud dataflow jobs run \
--gcs-location=gs://df-ts/latest/PubsubToBigQuery \
--parameters inputTopic=X outputTable=Y
```

Google-provided templates documentation



How-to guides
- All how-to guides
- Installing the SDK
- Creating a pipeline
- Specifying execution parameters
- Deploying a pipeline
- Using the monitoring UI
- Using the command-line interface
- Using Stackdriver Monitoring
- Logging pipeline messages
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SEND FEEDBACK

Contents
WordCount

Get started with Google-provided templates

Google provides a set of open-source Cloud Dataflow templates. For general information about templates, see the Overview page. To get started, use the WordCount template documented in the section below. See other Google-provided templates:

Streaming templates - Templates for processing data continuously:

- Cloud Pub/Sub Subscription to BigQuery
- Cloud Pub/Sub Topic to BigQuery
- Cloud Pub/Sub to Cloud Pub/Sub
- Cloud Pub/Sub to Cloud Storage Avro
- Cloud Pub/Sub to Cloud Storage Text
- Cloud Storage Text to BigQuery (Stream)
- Cloud Storage Text to Cloud Pub/Sub (Stream)
- Data Masking/Tokenization using Cloud DLP from Cloud Storage to BigQuery (Stream)

Batch templates - Templates for processing data in bulk:

- Cloud Bigtable to Cloud Storage Avro
- Cloud Bigtable to Cloud Storage SequenceFiles
- Cloud Datastore to Cloud Storage Text
- Cloud Spanner to Cloud Storage Avro
- Cloud Spanner to Cloud Storage Text
- Cloud Storage Avro to Cloud Bigtable

Which means now you can...

- Launch Dataflow jobs programmatically (via API).
- Launch Dataflow jobs instantaneously.
- Re-use Dataflow jobs.
- Letting you customize the execution of your pipeline.

What if you want to create your own template?

1. Modify pipeline options with ValueProviders.
2. Generate template file.

```
mvn compile exec:java \
 -Dexec.mainClass=com.example.myclass \
 -Dexec.args="--runner=DataflowRunner \
              --project=[YOUR_PROJECT_ID] \
              --stagingLocation=gs://[YOUR_BUCKET_NAME]/staging \
              --output=gs://[YOUR_BUCKET_NAME]/output \
              --templateLocation=gs://[YOUR_BUCKET_NAME]/templates/MyTemplate"
```

3. Call it from an API.

```
POST https://dataflow.googleapis.com/v1b3/projects/[YOUR_PROJECT_ID]/templates:launch?gcsPath=gs://[
{
    "jobName": "[JOB_NAME]",
    "parameters": {
        "inputFile" : "gs://[YOUR_BUCKET_NAME]/input/my_input.txt",
        "outputFile": "gs://[YOUR_BUCKET_NAME]/output/my_output"
    },
    "environment": {
        "tempLocation": "gs://[YOUR_BUCKET_NAME]/temp",
        "zone": "us-central1-f"
    }
}
```

Templates require modifying parameters for runtime

Python

```
class WordcountOptions(PipelineOptions):
    @classmethod
    def _add_argparse_args(cls, parser):
      parser.add_value_provider_argument(
          '--input',
          default='gs://dataflow-samples/shakespeare/kinglear.txt',
          help='Path of the file to read from')
      parser.add_argument(
          '--output',
          required=True,
          help='Output file to write results to.')
  pipeline_options = PipelineOptions(['--output', 'some/output_path'])
  p = beam.Pipeline(options=pipeline_options)

  wordcount_options = pipeline_options.view_as(WordcountOptions)
  lines = p | 'read' >> ReadFromText(wordcount_options.input)
```

Run-time parameters

Non run-time parameters can stay

Runtime parameters must be modified.

Creating a template

- ValueProviders are passed down throughout the whole pipeline construction phase
- ValueProvider.get() only available in processElement()
    - Because it is fulfilled via API call

```
public interface SumIntOptions extends PipelineOptions {
    // New runtime parameter, specified by the --int
    // option at runtime.
    ValueProvider<Integer> getInt();
    void setInt(ValueProvider<Integer> value);
}

class MySumFn extends DoFn<Integer, Integer> {
    ValueProvider<Integer> mySumInteger;

    MySumFn(ValueProvider<Integer> sumInt) {
        // Store the value provider
        this.mySumInteger = sumInt;
    }

    @ProcessElement
    public void processElement(ProcessContext c) {
       // Get the value of the value provider and add it to
       // the element's value.
       c.output(c.element() + mySumInteger.get());
    }
}

public static void main(String[] args) {
  SumIntOptions options =
        PipelineOptionsFactory.fromArgs(args).withValidation()
          .as(SumIntOptions.class);
```

Nested Value Providers

```
public static void main(String[] args) {
  pipeline
    .apply(Create.of(1, 2, 3).withCoder(BigEndianIntegerCoder.of()));
    // Write to the computed complete file path.
    .apply("OutputNums", TextIO.write().to(NestedValueProvider.of(
      options.getFileName(),
      new SerializableFunction<String, String>() {
        @Override
        public String apply(String file) {
          return "gs://bucket/" + file;
        }
      })));

  pipeline.run();
}
```

Template metadata

Located at the same directory, named <template_name>_metadata

```
{
  "name": "WordCount",
  "description": "An example pipeline that counts words in the input file.",
  "parameters": [{
    "name": "inputFile",
    "label": "Input Cloud Storage File(s)",
    "help_text": "Path of the file pattern glob to read from.",
    "regexes": ["^gs:\/\/[^\n\r]+$"],
    "is_optional": true
  },
  {
    "name": "output",
    "label": "Output Cloud Storage File Prefix",
    "help_text": "Path and filename prefix for writing output files. ex: gs://MyBucket/counts",
    "regexes": ["^gs:\/\/[^\n\r]+$"]
  }]
}
```

Summary

Dataflow versus Dataproc

Building Dataflow pipelines in code

Key considerations with designing pipelines

Transforming data with PTransforms

Aggregating with GroupByKey and Combine

Side inputs and windows of data

Creating and reusing Pipeline Templates