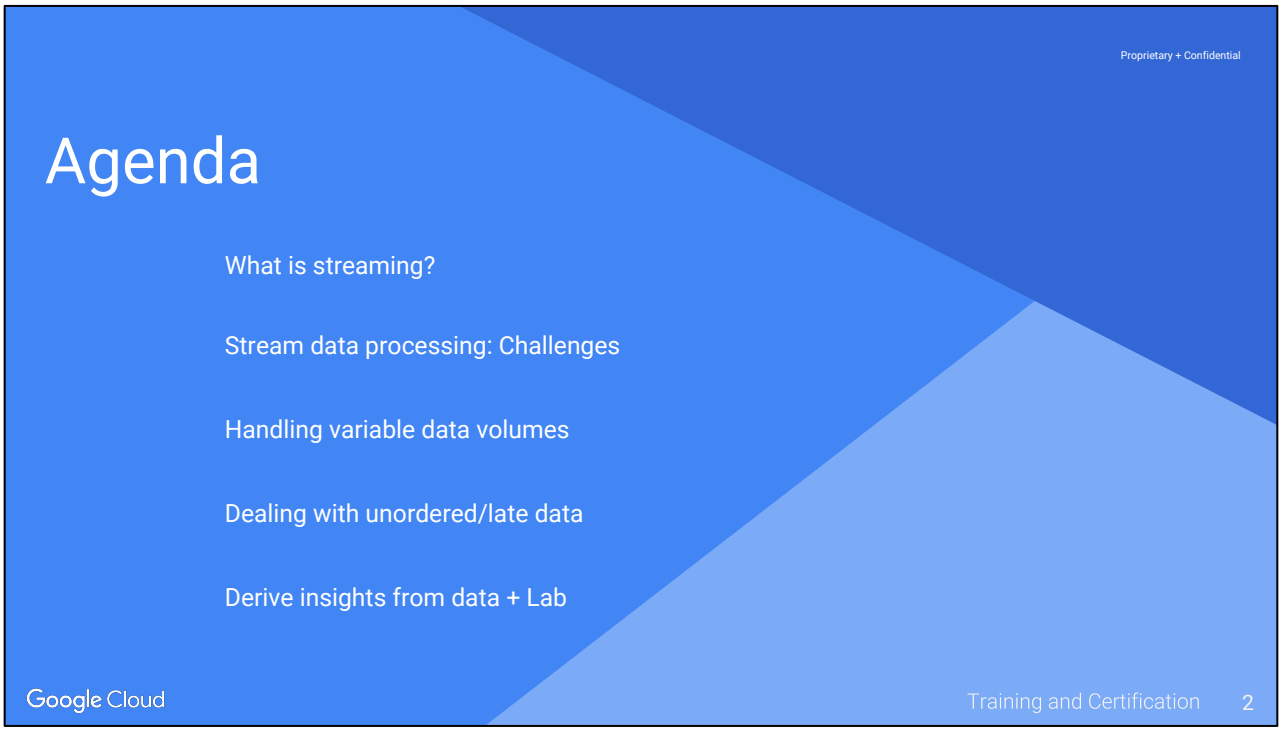
Google Cloud

Architecture of streaming analytics pipelines

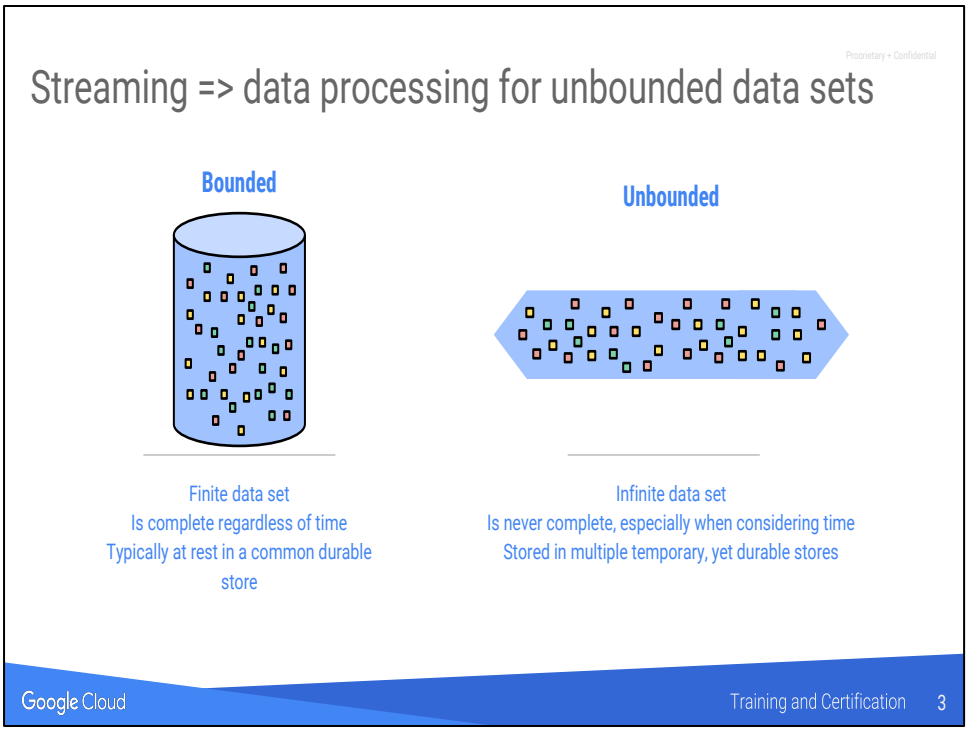
Data Engineering on Google Cloud Platform

1 hour



Notes:

This course discusses what stream processing is, how it fits into a big data architecture, when stream processing makes sense, and what Google Cloud technologies and products you can choose from to build a resilient streaming data processing solution.



Notes:

Streaming is basically data processing on unbounded data. Bounded data is data at rest. Stream processing is how you deal with unbounded data.

Without streaming data….there'd be no stream processing. Streaming is an execution engine (system, service, runner) capable of processing unbounded data.

When designed correctly a streaming processing engine can provide: low latency, speculative or partial results, the ability to flexibly reason about time, controls for correctness, and the power to perform complex analysis.

Notes:

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In this course, we use the San Diego traffic data collected over a year. So this is data that is bounded. However, we are gonna simulate as if it were streaming real time.

Should We Replace the Term Big Data with “Unbounded Data”?

Clive Longbottom of Quocirca makes the case that “Big Data” is the wrong way to talk about the changes in the ways we store, manage and process data. The term certainly gets thrown around alot, and in many cases for talking about managing data that is much smaller than the petabytes of data that arguably defines big data. Longbottom suggests the term “unbounded data”

http://readwrite.com/2011/03/25/big-data-round-up-unbounded-da/

The need for fast decisions leads to streaming

Massive data, from varied sources, that keeps growing over time

Need to derive insights immediately in the form of dashboards

How many sales did I make in the last hour due to advertising conversion?

Which version of my web page do people like better?

Which transactions look fraudulent?

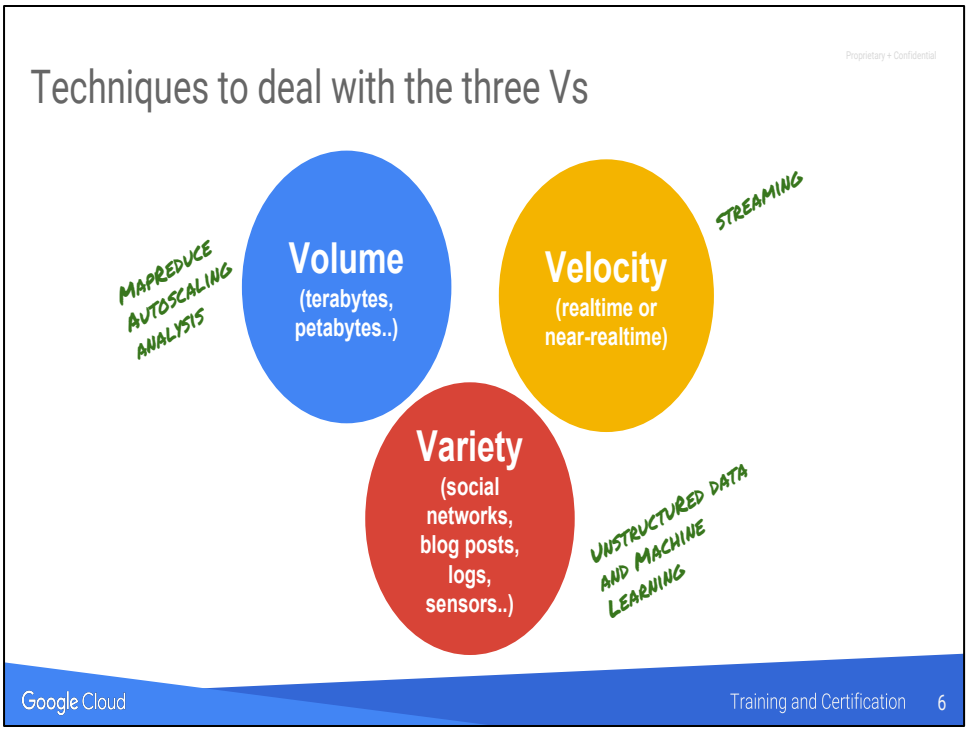
Need to make timely decisions

Notes:

- The demand for stream processing is increasing a lot these days…..processing big volumes of data is not enough
- Data has to be processed fast, so that a firm can react to changing business conditions in real time.
- Real world stream processing use cases include trading, fraud detection, system monitoring, smart order routing, transaction cost analysis….the list is long.

We talk about streaming unbounded data, we wanna derive insights. Which version of my web page ppl like...say ur running AB test..that's streaming.

Batch vs Stream: If you wanna look for fraud transactions 3 days ago….that's batch. If u wanna look at it as it happens...that's streaming.



Notes:

We have terabytes and petabytes of data...and how we deal with it….we talked about on day 1….mapreduce. We talked about batch processing over volumes of data. Variety is all sorts….audio video etc….and we talked about ML APIs. The third part is real real time.

A big data architecture contains several parts. Often, masses of structured and semi-structured historical data are stored in Cloud storage/PubSub/BigQuery (Volume + Variety). On the other side, stream processing is used for fast data requirements (Velocity + Variety). Both complement each other very well. Internet of Things has increased volume, variety and velocity of data, leading to a dramatic increase in the applications for stream processing technologies.

MApReduce -> volume
Velocity -> streaming
Variety - > ML

Agenda

Stream data processing: Challenges

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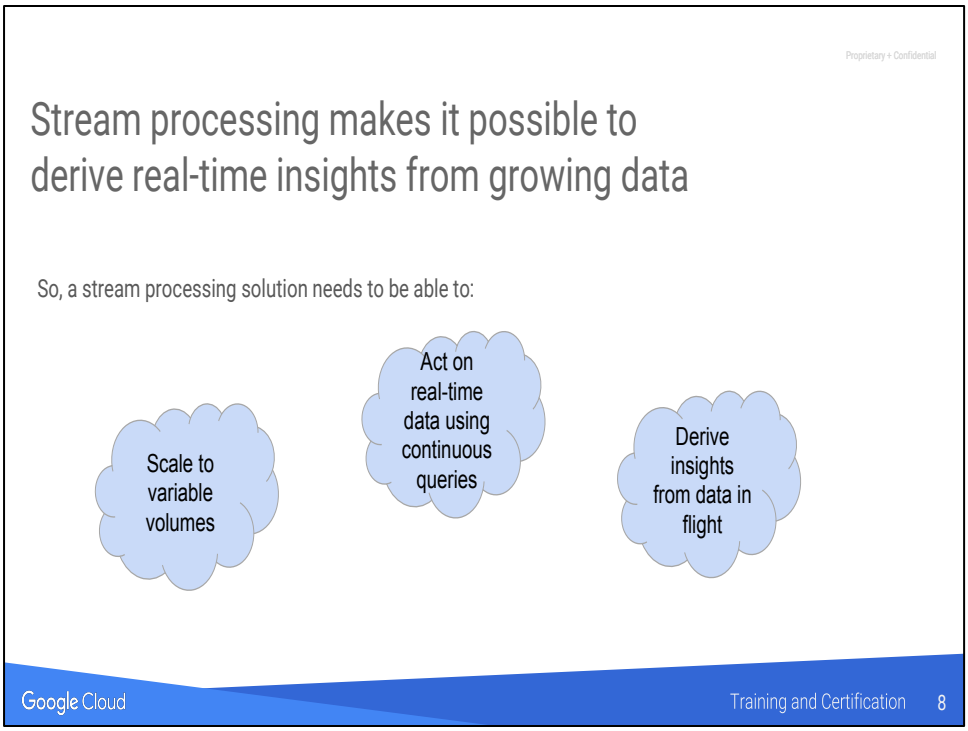


Notes:
Has to be able to scale...think of credit cards, there will be hundreds of transactions happening all the time. Continuous query….do the query on last hour of data.
Stream processing systems were born nearly a decade ago, due to the need for low-latency processing of large volumes of highly dynamic, time-sensitive continuous streams of data from sensor-based monitoring devices and alike.

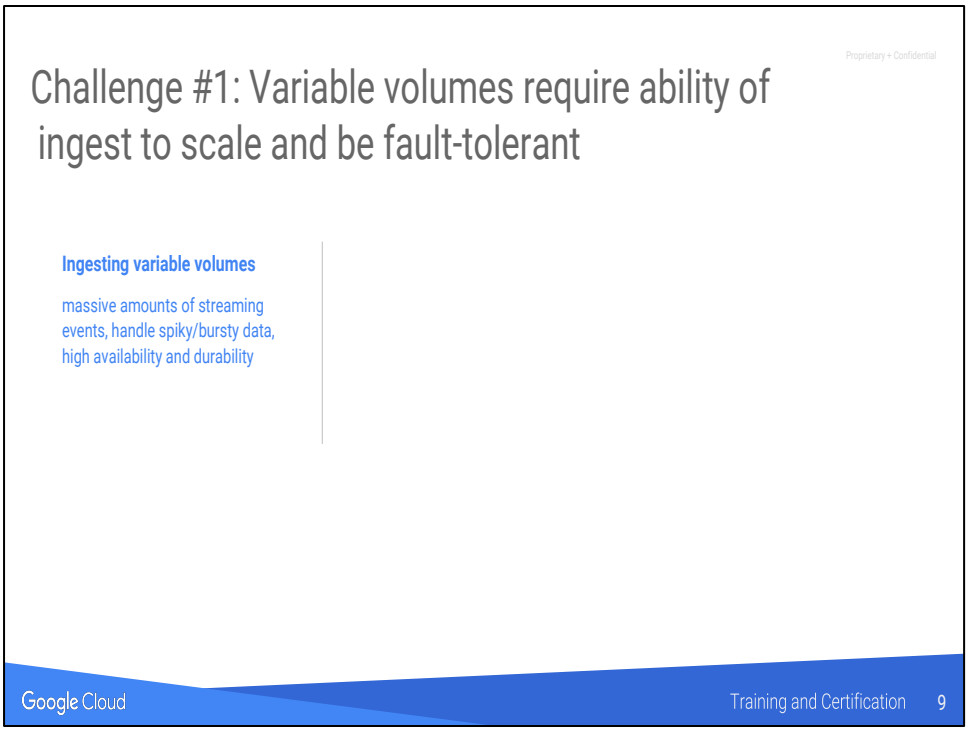
Stream processing found its first uses in the finance industry, as stock exchanges moved from floor-based trading to electronic trading. Today, it makes sense in almost every industry - anywhere where you generate stream data through human activities, machine data or sensors data.

Traditional “Store-and-Pull” model of traditional data processing systems was simply not suitable for the high performance needs of the streaming applications, where data was much more dynamic than queries and had to be processed on the fly. Consequently, this change of roles between data and queries led to an upside down architecture, and thus, to Stream Processing Engines

Scale to variable volumes, be highly available and fault tolerant

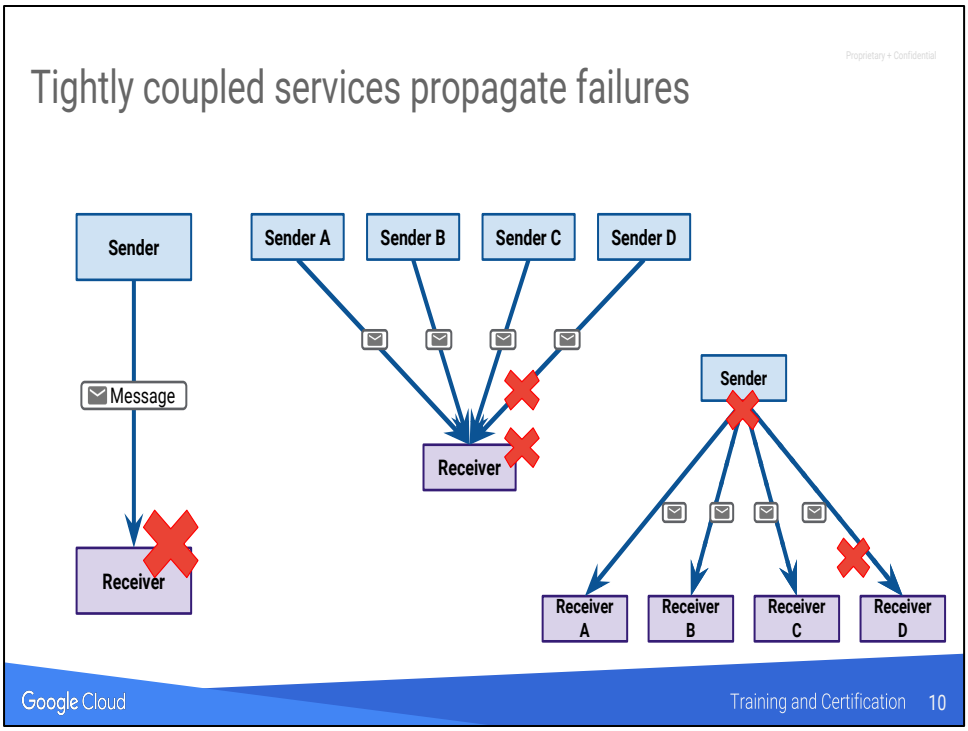
Act on real-time data using “continuous queries”
(i.e., SQL-type queries that operate over time and buffer windows)

Derive Insights from data in flight
(continuously calculate mathematical or statistical analytics on the fly within the stream while accounting for late, out-of-order data)



Notes:

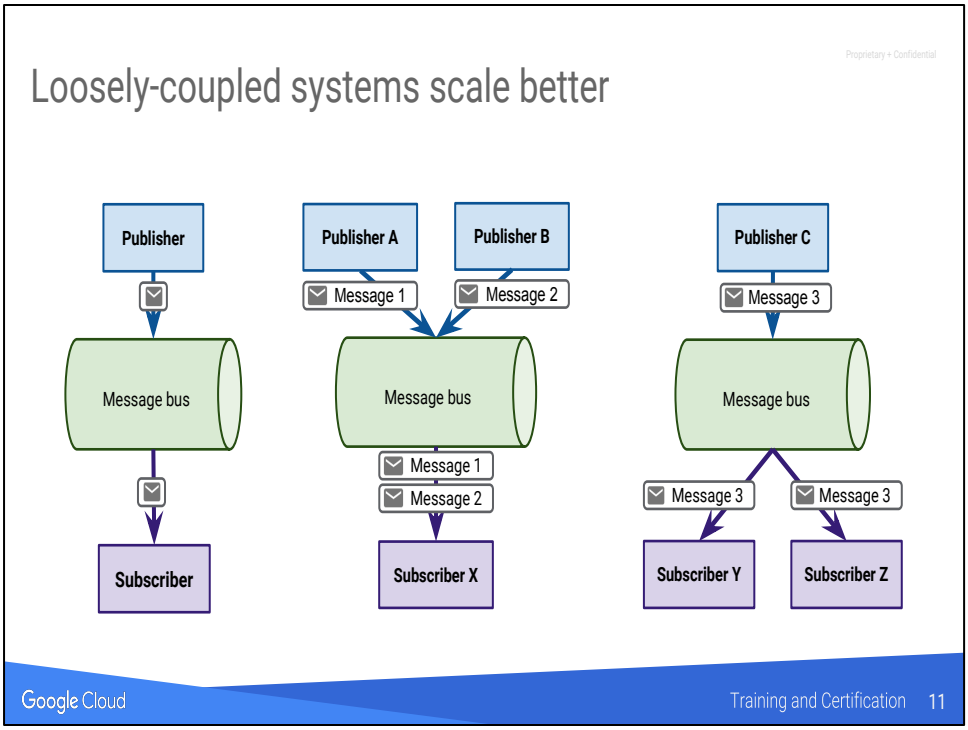
Scaling implies being able to deal with faults as clients/servers fail unexpectedly.



Notes:

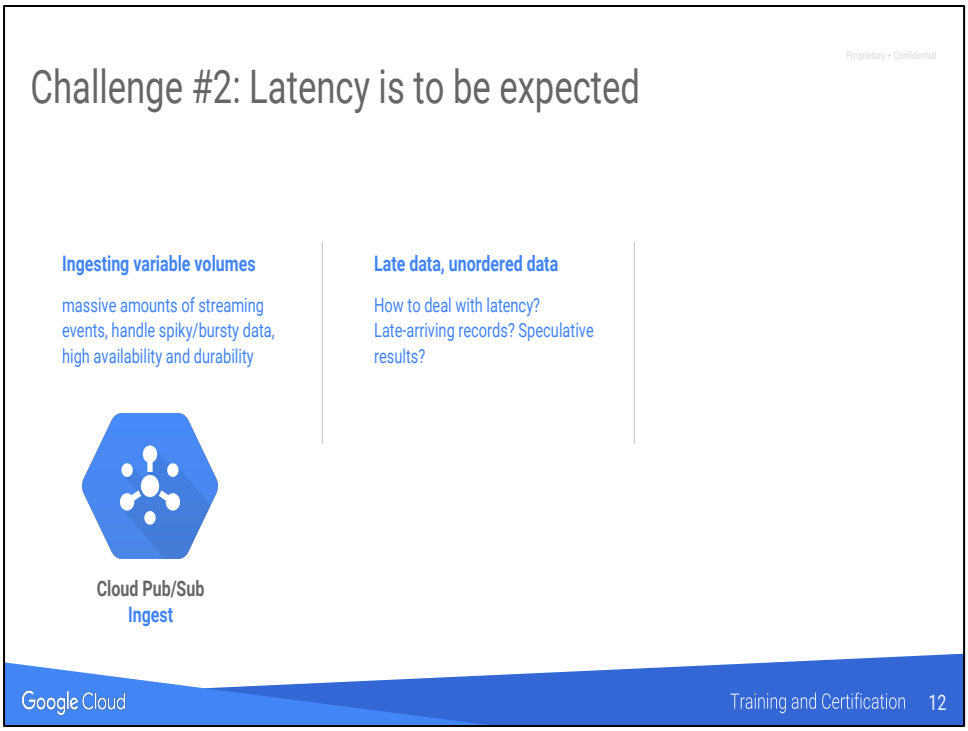
One way is to send directly…..may not be able to handle volume…..single receiver is problem when receiver is down. Tight coupling means errors will propagate. Starts with one….then whole ecosystem gets buggy.

What happens if Sender B has to send a message but Receiver is down? Or what if Sender sends the data and there is a connection failure?". Pub/Sub takes care of these things. Once the sender pushes the message to Pub/Sub, it becomes Pub/Sub's responsibility to take care of knowing if/when the Receiver is available and to retry until the message is acknowledged. If one component is down, the rest of the system can keep working as usual, and the broker will make sure messages are safely sent whenever possible.



Notes:

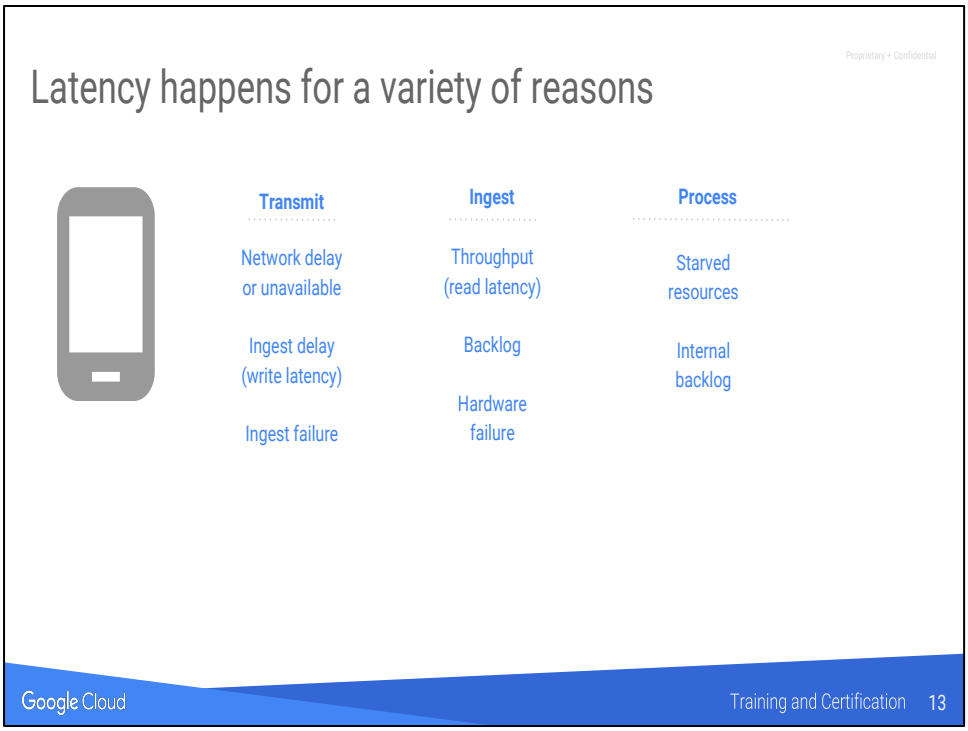
Solution to this is buffering. Not send it directly...but sending it to a message bus...that can handle volumes. All scenarios fan-in, fan-out will work.



Notes:

Streaming data can be late and unordered: Let's detail these challenges and how Cloud Dataflow can help address them

There is always danger with latency. If 2 windmills are sending in data...one may come before another. Or even out of order. You compute result.....then data that was supposed to be in result comes in.



Notes:

You have to operate assuming latency will happen.

2 school of thoughts: .one says let’s harden our system so no error happens

Another says let's design so that errors will happen but we will be resilient. Latency will happen...fact of life.

When you design processing pipeline….assume it may have unordered….latency and come up with ways to address it.

Beam/Dataflow model provides exactly once processing of events

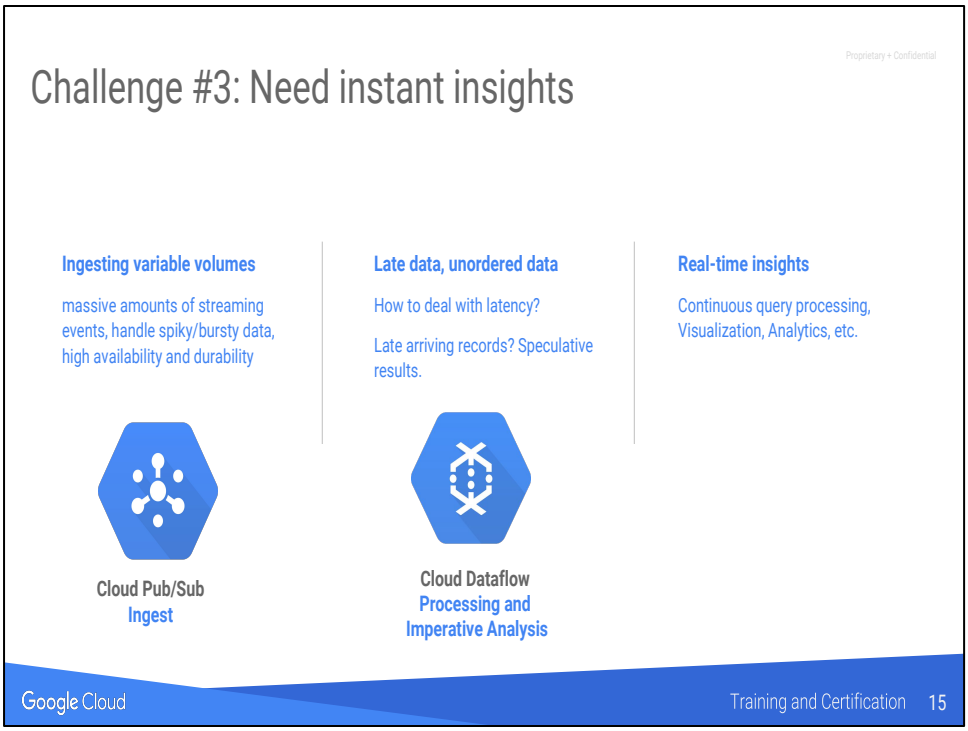
- ***What*** **results are calculated?** Answered via transformations.
- ***Where*** **in event time are results calculated?** Answered via event-time windowing.
- ***When*** **in processing time are results materialized?** Answered via watermarks, triggers, and allowed lateness.
- ***How*** **do refinements of results relate?** Answered via accumulation modes

https://cloud.google.com/blog/big-data/2017/05/after-lambda-exactly-once-processing-in-google-cloud-dataflow-part-1

The Dataflow model lets you write clean, modular code that evolves beautifully over time as needs change and expand. The model maps directly onto the four questions that are relevant in any out-of-order data processing pipeline:

- ***What*** **results are calculated?** Answered via transformations.
- ***Where*** **in event time are results calculated?** Answered via event-time windowing.
- ***When*** **in processing time are results materialized?** Answered via watermarks, triggers, and allowed lateness.
- ***How*** **do refinements of results relate?** Answered via accumulation modes

In addition, the powerful out-of-order processing constructs in our model, such as watermarks and triggers, allow you to maintain eventual correctness of results within a single pipeline, while also offering low-latency speculation, the ability to refine results after the fact when upstream data change, and an easy way to cap the useful lifetime of data within your system.


Proprietary + Confidential
Challenge #3: Need instant insights
Ingesting variable volumes
massive amounts of streaming events, handle spiky/bursty data, high availability and durability
Late data, unordered data
How to deal with latency?
Late arriving records? Speculative results.
Real-time insights
Continuous query processing, Visualization, Analytics, etc.
Cloud Pub/Sub
Ingest
Cloud Dataflow
Processing and Imperative Analysis
Google Cloud
Training and Certification
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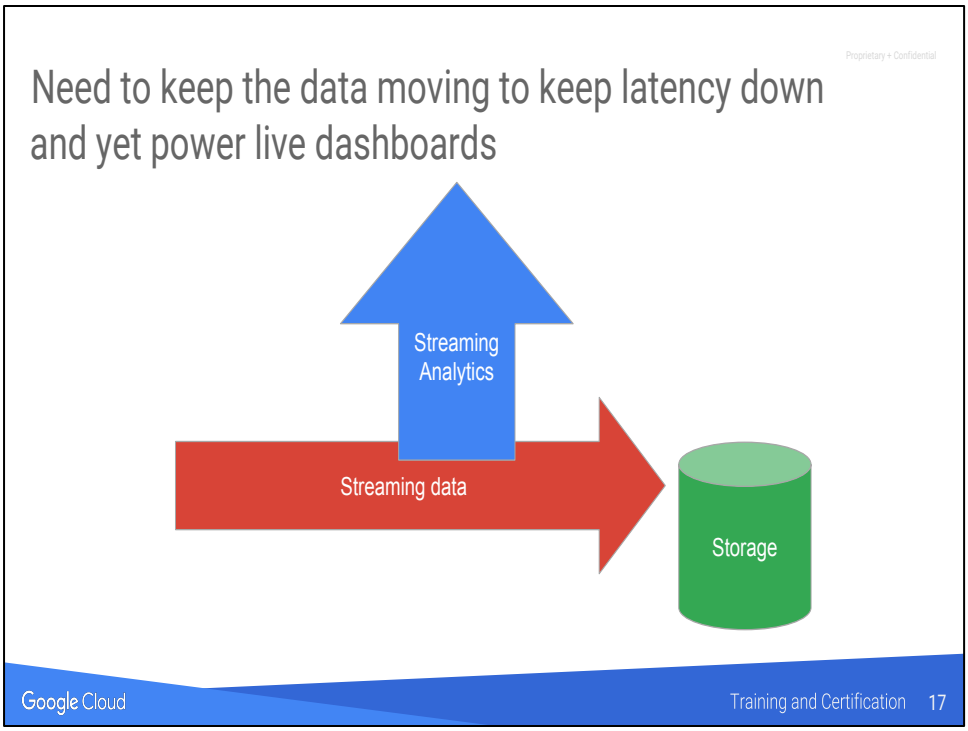
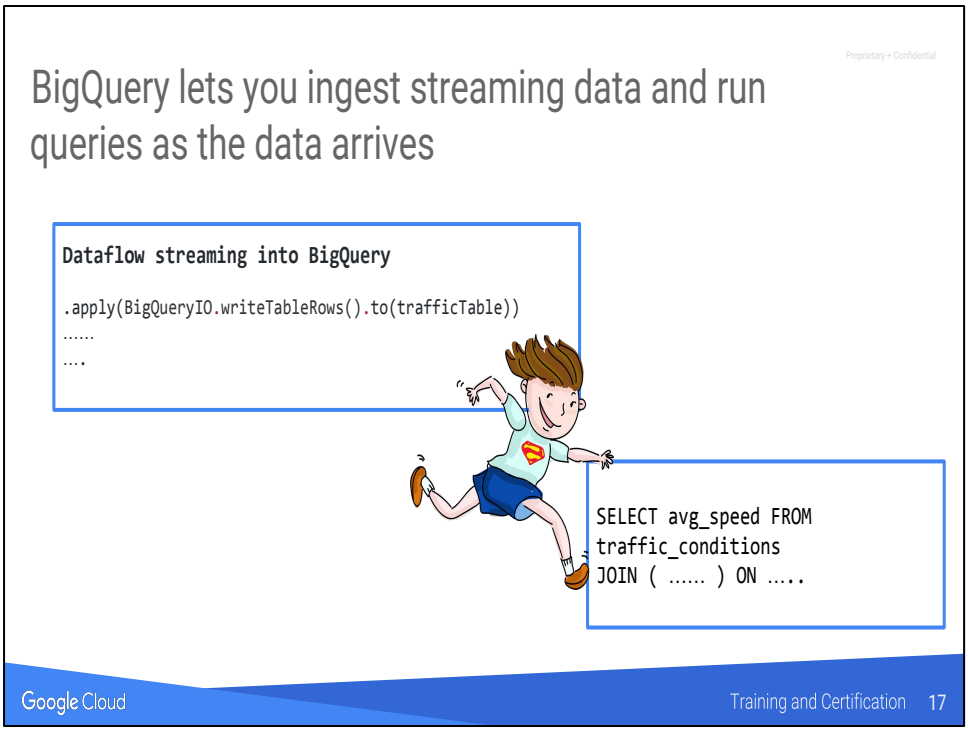


Notes:

To achieve low latency, a system must be able to perform message processing without having a costly storage operation in the critical processing path. A storage operation adds a great deal of unnecessary latency to the process (e.g., committing a database record requires a disk write of a log record). For many stream processing applications, it is neither acceptable nor necessary to require such a time-intensive operation before message processing can occur. Instead, messages should be processed “in-stream” as they fly by.

Source: http://cs.brown.edu/~ugur/8rulesSigRec.pdf

Example:
Processing 300 million messages, at about 300K messages per second and outputting aggregates and alerts periodically, and store them on BigQuery for further analytics. The aggregates and aggregates alerts are calculated on the fly by Dataflow/Beam. If the data was first committed to storage before calculating aggregates, the extra milliseconds for 300K events per second could become and issue.Dataflow/Beam can work reliably with those kind of events at that level of throughput without having to save the data first.



Notes:

We looked at bigquery as a batch system….here we look at its streaming capability

Provided by the APIs tabledata().insertAll() method

Works for partitioned and standard tables

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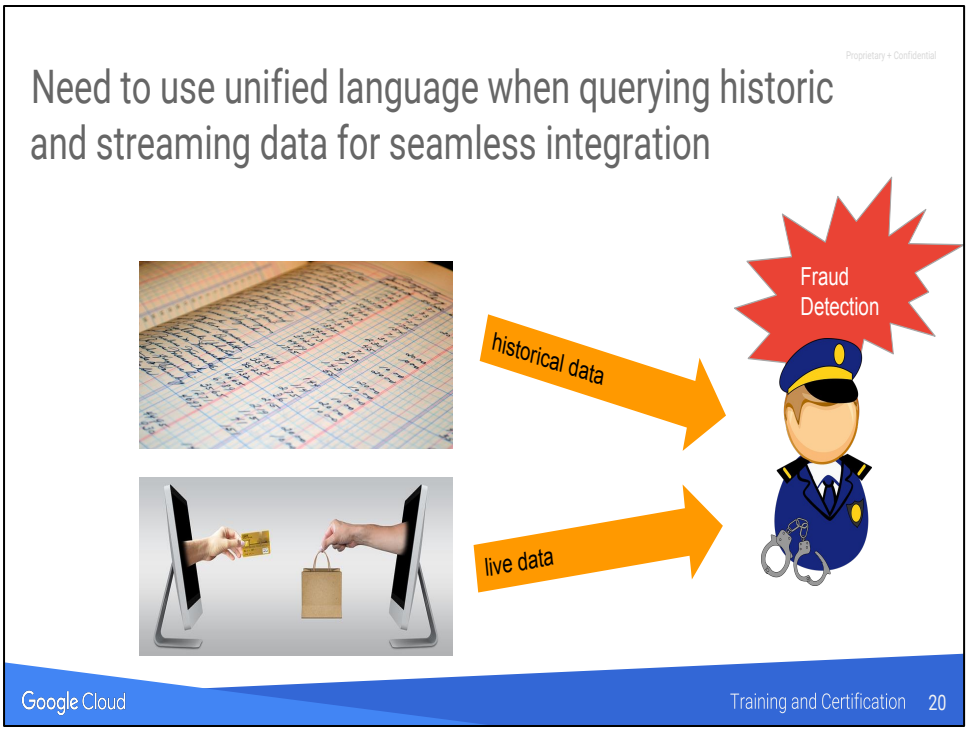

Notes:

A system that can deal with reference data and live streaming data if you want real time insight

For example, in on-line data mining applications (such as detecting credit card or other transactional fraud), identifying whether an activity is “unusual” requires, by definition, gathering the usual activity patterns over time, summarizing them as a “signature”, and comparing them to the present activity in real time. To realize this task, both historical and live data need to be integrated within the same application for comparison.

For low-latency streaming data applications, interfacing with a client-server database connection to efficiently store and access persistent state will add excessive latency and overhead to the application. Therefore, state must be stored in the same operating system address space as the application using an embedded database system.

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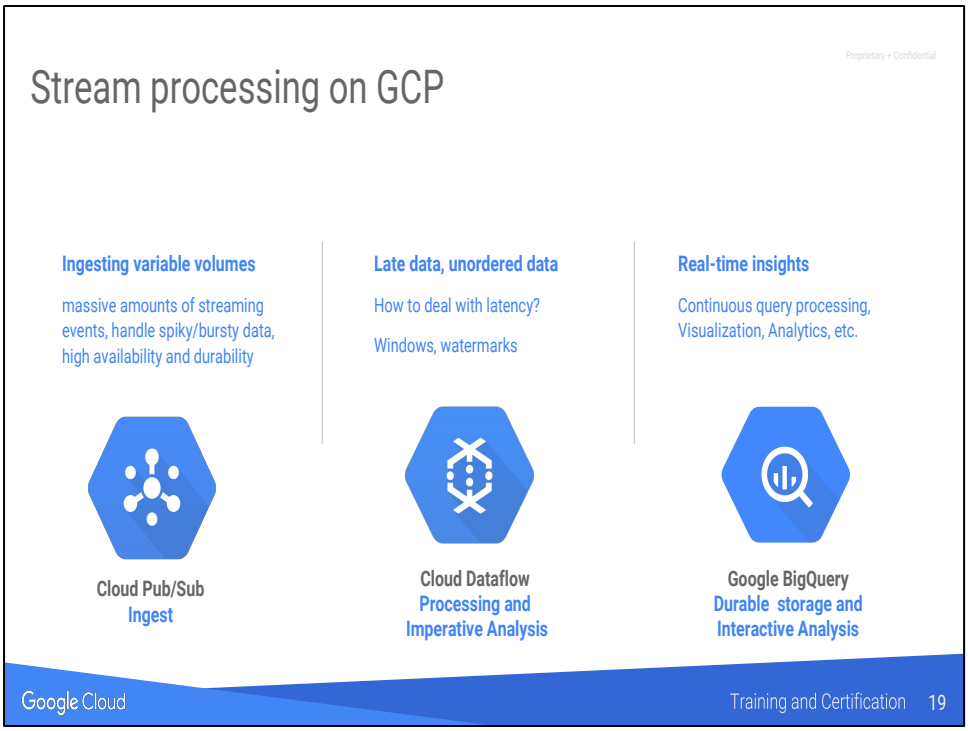


Notes:

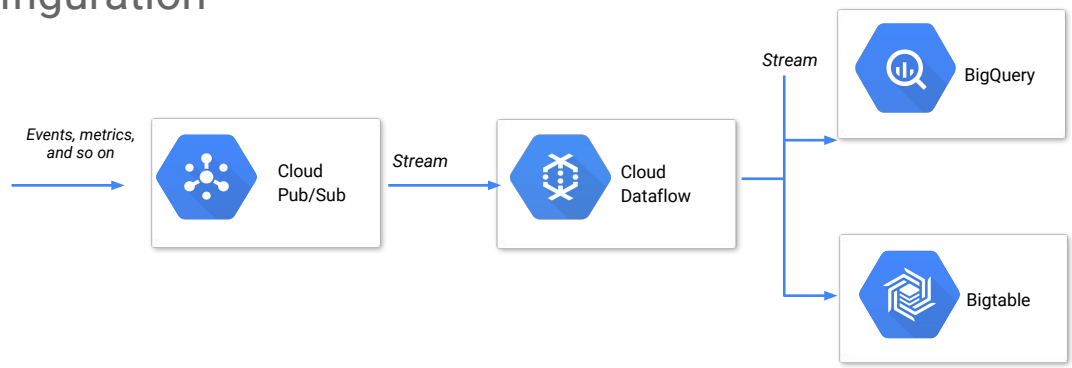
PubSub is your global message bus.

Dataflow is capable of doing batch and streaming ….code does not change.

BigQuery gives you power of analytics.

BigTable when you get overwhelming volume.

Stream data processing on GCP: A common configuration



Fully managed, No-ops services

Notes:

PubSub is your global message bus

Dataflow is capable of doing batch and streaming ….code does not change

BigQuery gives you power of analytics

BigTable when you get overwhelming volume

Bigquery is order of seconds, sql,

While bigtable is order of ms, nosql

Data sources – source of data streams. This is the raw data and so the source of truth. A data source could be a sensor network, or a mobile application, or a web client, or a log from a server, or even a thing from Internet of Things.

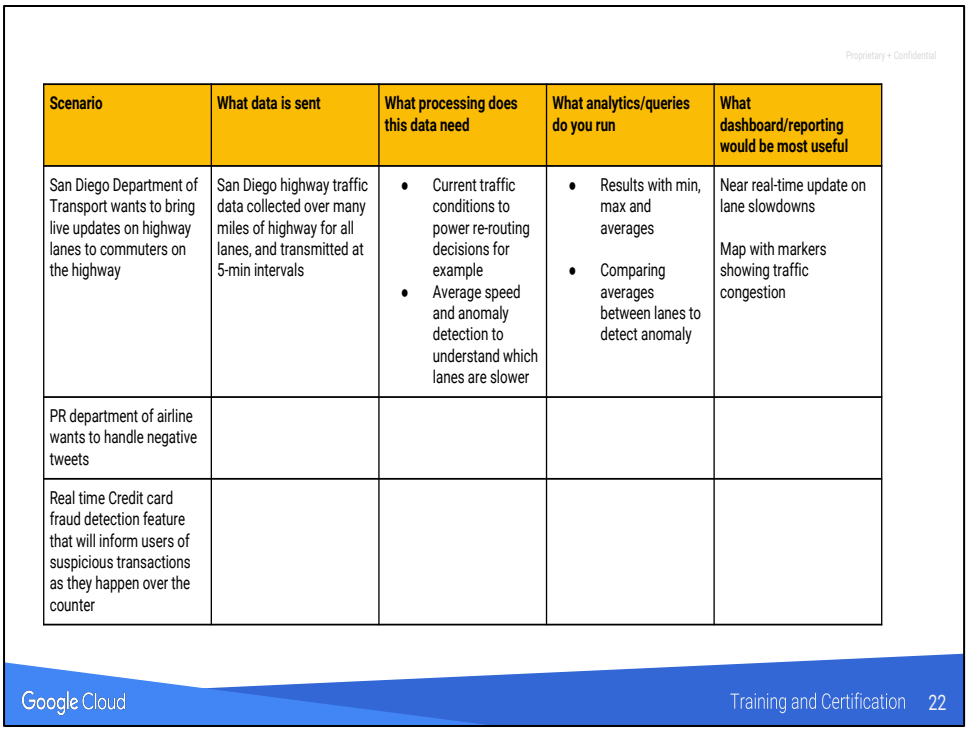
Message bus – reliable, high-throughput and low latency messaging system.

Stream processing system – a computational framework capable of doing computations on data streams. There a few stream processing frameworks out there.

Analytic Environment – processed data is of no use if it does not serve end applications or users with real-time insights

End applications – Dashboards, Reports, Decision Makers

Lab:
Discuss some streaming scenarios

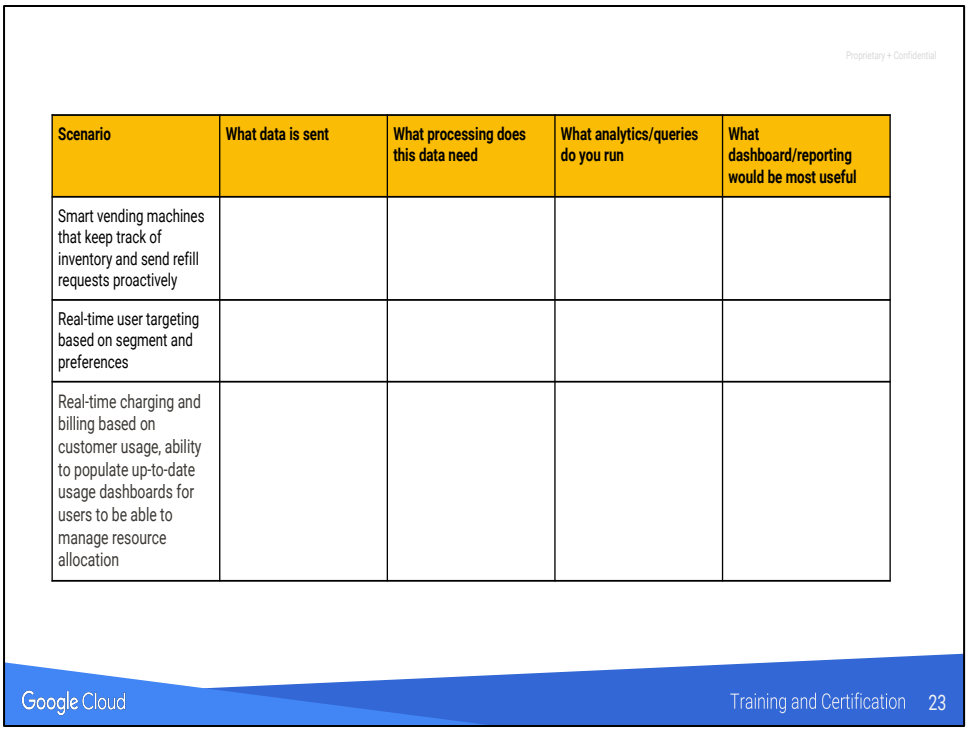


Notes:

Talk through the first scenario since labs are based on it. Then have them jot down answers individually. Then discuss as a group. This looks trivial, but turns out to be quite hard, especially if you are not used to thinking about the full journey, from scenario to data pipeline to dashboards. Suggest ~10 minutes to fill out the table (2 minutes per row).

PR example:
Tweets that mention airline name or hashtag
Sentiment analysis, entity detection for topics (“delay”, “weather”, “baggage”, “flight attendant”, etc.) and location
dashboard top 10 negative topics segregated different ways.

Fraud example: data-transactions from every terminal in the world, processing-segregate by user,country, store, who to notify, queries-are we seeing increase in fraudulent activity in London, Dashboards - todays query is tomorrows dashboard



Vending machine:

Data: purchases processing: time between successive purchases, analytics: estimate how long inventory will last dashboard:


cloud.google.com
Image by Connie Zhou