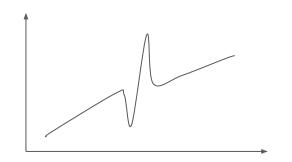
Eventually, time will kill your data pipeline

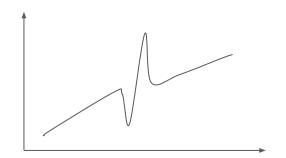
Berlin Buzzwords, 2019-06-17 Lars Albertsson Mimeria

1



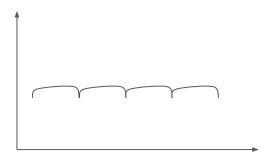
"Time is out of joint. O cursed spite, That ever I was born to set it right."

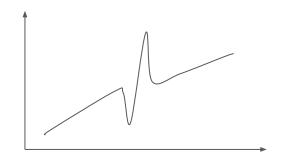
- Hamlet, prince of Denmark



"Time is out of joint. O cursed spite, That ever I was born to set it right."

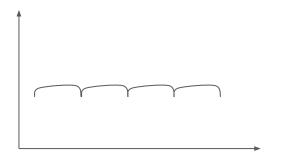
- Hamlet, prince of Denmark

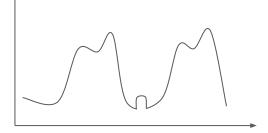


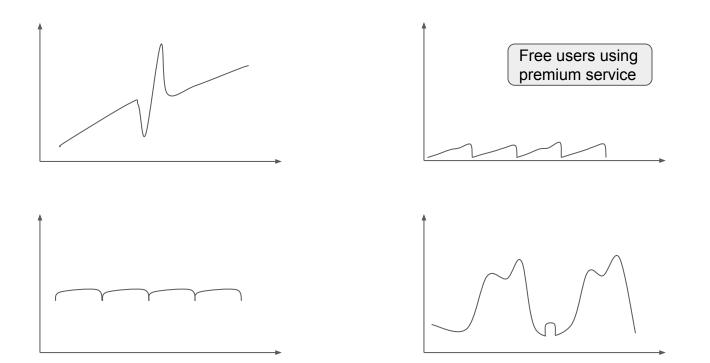


"Time is out of joint. O cursed spite, That ever I was born to set it right."

- Hamlet, prince of Denmark







Time will kill us all

- Time handling causes data processing problems
- Observed issues
- Principles, patterns, anti-patterns

Goals:

- Awareness, recognition
- Tools from my toolbox

Data categories, time angle

• Facts

- Events, observations
- Time stamped by clock(s)
- Continuous stream

Data categories, time angle

• Facts

- Events, observations
- Time stamped by clock(s)
- Continuous stream

• State

- Snapshot view of system state
- Lookup in live system. Dumped to data lake.
- Regular intervals (daily)

Data categories, time angle

• Facts

- Events, observations
- Time stamped by clock(s)
- Continuous stream

• State

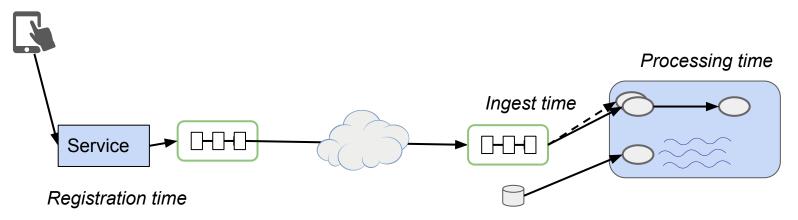
- Snapshot view of system state
- Lookup in live system. Dumped to data lake.
- Regular intervals (daily)

• Claims

- Statement about the past
- Time window scope

Time scopes

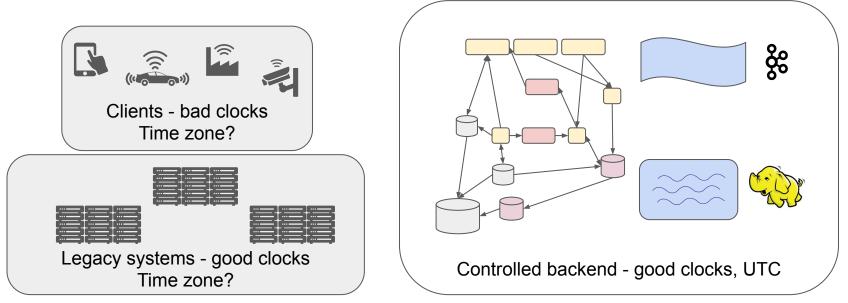
Event time



Domain time - scope of claim. "These are suspected fraudulent users for March 2019."

Clocks

- Computer clocks measure elapsed time
- Good clocks, bad clocks, wrong clocks



Calendars, naive

Maps time to astronomical and social domains

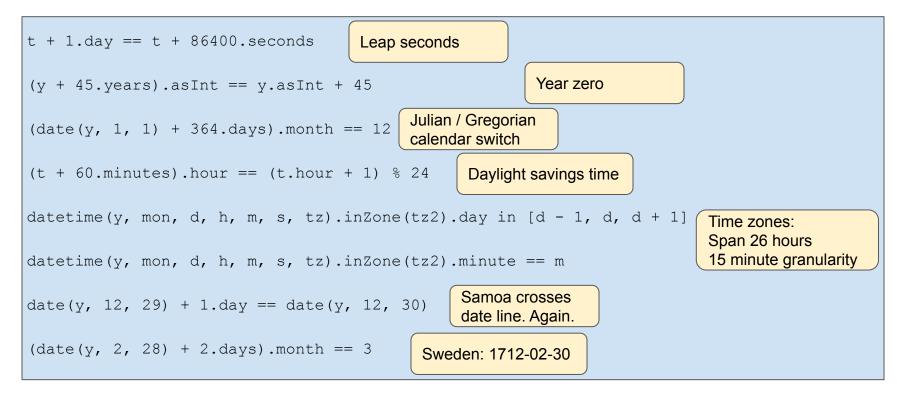
Naive calendar

- 365 days + leap years
- 12 months, weird number of days
- 7 day weeks
- 24 hours
- 60 minutes
- 60 seconds
- 24 hour time zones

Naive calendar properties

```
t + 1.day == t + 86400.seconds
                                                                Can you find the counter
(y + 45.years).asInt == y.asInt + 45
                                                                examples?
(date(y, 1, 1) + 364.days).month == 12
(t + 60.minutes).hour == (t.hour + 1) % 24
datetime(y, mon, d, h, m, s, tz).inZone(tz2).day in [d - 1, d, d + 1]
datetime(y, mon, d, h, m, s, tz).inZone(tz2).minute == m
date(y, 12, 29) + 1.day == date(y, 12, 30)
(date(y, 2, 28) + 2.days).month == 3
```

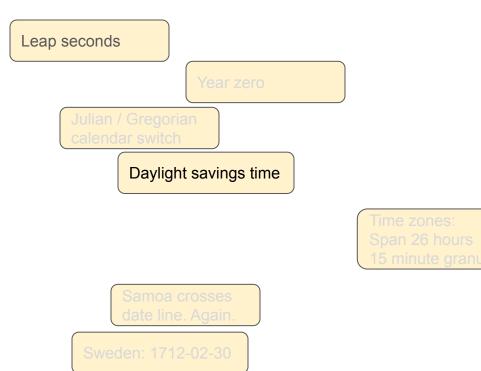
Calendar reality



Small problems in practice

Except DST

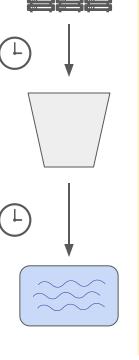
- Analytics quality
- Changes with political decision
- Might affect technical systems
- (Affects health!)



Typical loading dock ingress

- File arrives every hour
- Ingest job copies to lake, applies data platform conventions
- Source system determines format, naming, and

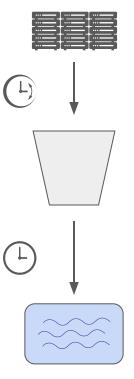
timestamps

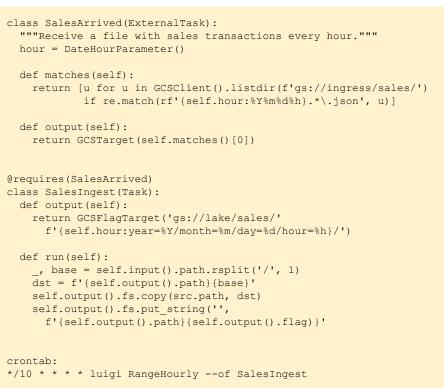


```
class SalesArrived(ExternalTask):
  """Receive a file with sales transactions every hour."""
  hour = DateHourParameter()
  def matches(self):
    return [u for u in GCSClient().listdir(f'qs://ingress/sales/')
            if re.match(rf'{self.hour:%Y%m%d%h}.*\.json', u)]
  def output(self):
    return GCSTarget(self.matches()[0])
@requires(SalesArrived)
class SalesIngest(Task):
  def output(self):
   return GCSFlagTarget('gs://lake/sales/'
      f'{self.hour:vear=%Y/month=%m/dav=%d/hour=%h}/')
  def run(self):
    , base = self.input().path.rsplit('/', 1)
    dst = f'{self.output().path}{base}'
    self.output().fs.copy(src.path, dst)
    self.output().fs.put string('',
      f'{self.output().path}{self.output().flag)}'
crontab:
*/10 * * * * luigi RangeHourly --of SalesIngest
```

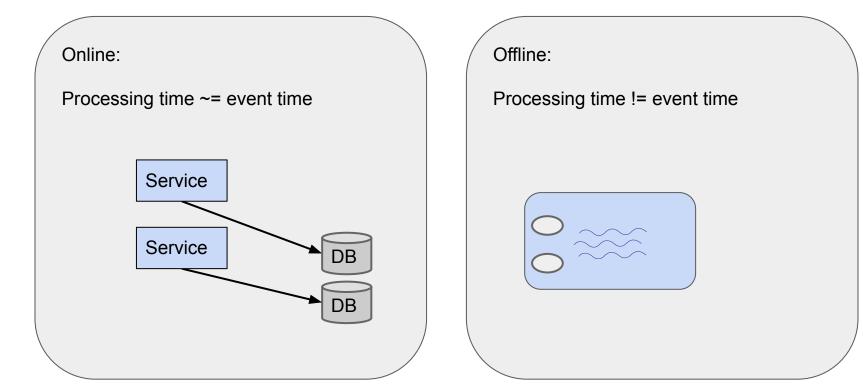
Typical loading dock ingress

- File arrives every hour
- Ingest job copies to lake, applies data platform conventions
- Source system determines format, naming, and
 - timestamps, *incl. zone*
- Spring: halted ingest Autumn: data loss





Offline / online



Batch job - functional principles

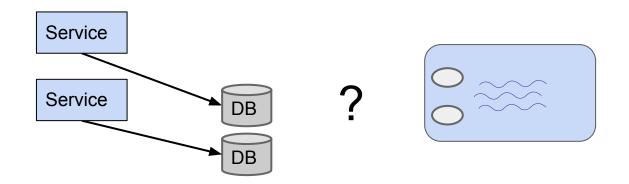
Job == function([input datasets]): [output datasets]

- Ideally: atomic, deterministic, idempotent
- No external factors \rightarrow deterministic
 - No (mutable) database queries
 - No service lookup
 - Don't read wall clock
 - No random numbers
- Known, bounded input data
- No orthogonal concerns & input factors
 - ─ Invocation
 - Scheduling
 - ← Input / output location
- No side-effects

DB	Service
X	X
(
\smile	

Database dumping

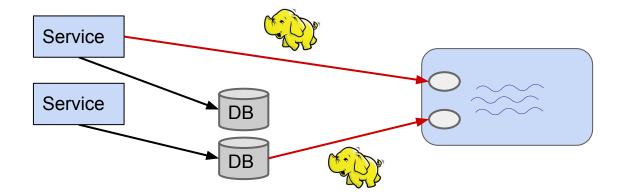
- Simple approach: Daily full table snapshot to cluster storage dataset.
- Easy on surface...



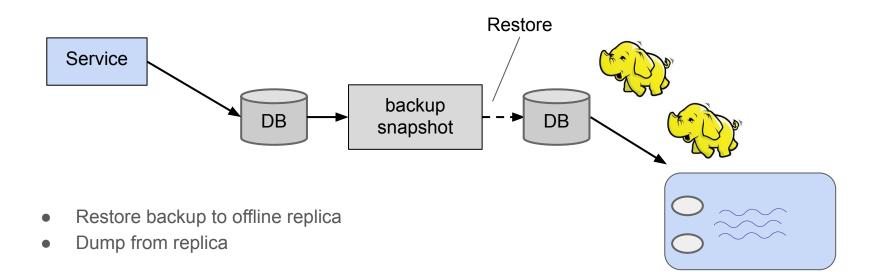
Anti-pattern: Death by elephant

Sqoop (dump with MapReduce) production DB
 MapReduce from production API

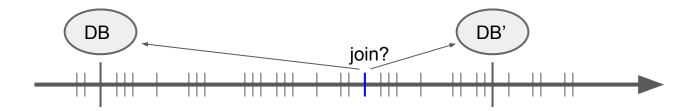
Hadoop / Spark == internal DDoS service



Pattern: Offline replica

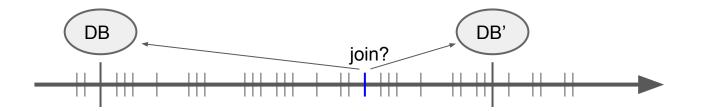


Using snapshots

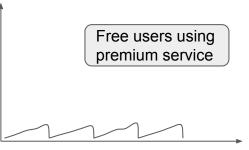


- join(event, snapshot) \rightarrow always time mismatch
- Usually acceptable
 - In one direction

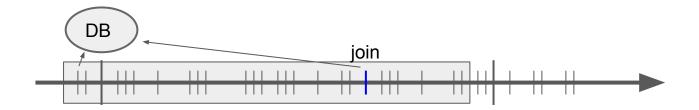
Using snapshots



- join(event, snapshot) \rightarrow always time mismatch
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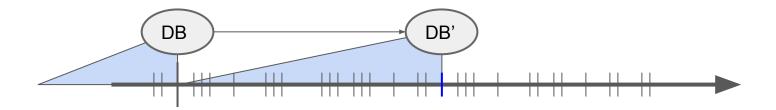


Window misalign



• Time mismatch in both directions

Event sourcing

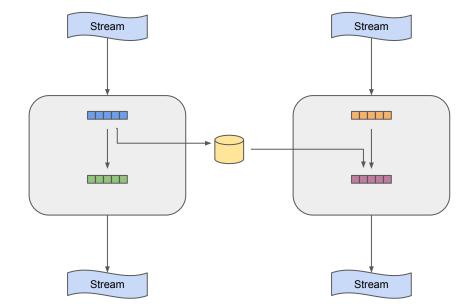


- Every change to unified log == source of truth
- snapshot(t + 1) = sum(snapshot(t), events(t, t+1))
- Allows view & join at any point in time
 - But more complex

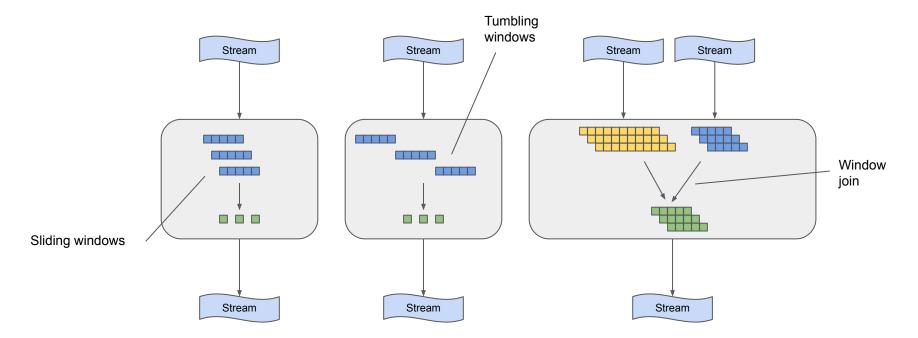
Easier to express with streaming?

state + event \rightarrow state'

- State is a view of sum of all events
 - \circ Join with the sum table
 - Beautiful!
 - Not simple in practice
- Mixing event time and processing time
 - Every join is a race condition

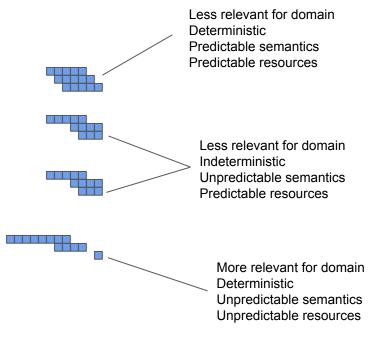


Stream window operations



Window over what?

- Number of events
- Processing time
- Registration time
- Event time



Event ingest

Batch is easier?

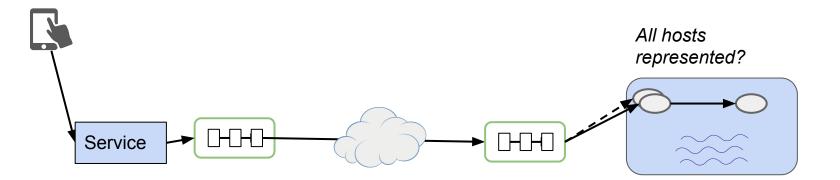
Yes But, some pitfalls When to start processing?

How to divide events to datasets?

Anti-pattern: Bucket by registration time

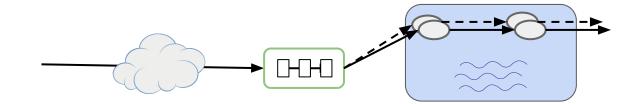
Ancient data collection:

- Events in log files, partitioned hourly
- Copy each hour of every host to lake



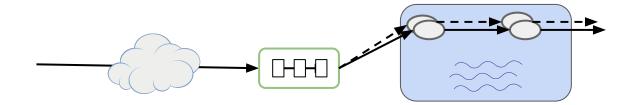
Anti-pattern: Reprocess

- Start processing optimistically
- Reprocess after x% new data has arrived



Supporting reprocessing

- Start processing optimistically
- Reprocess after x% new data has arrived



Solution space:

- Apache Beam / Google \rightarrow stream processing ops
- Data versioning
- Provenance

Requires good (lacking) tooling

Event collection

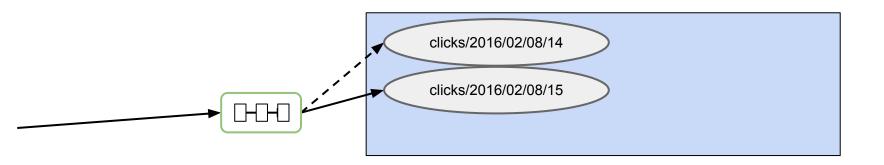
Event time

Processing time

Service

Registration time

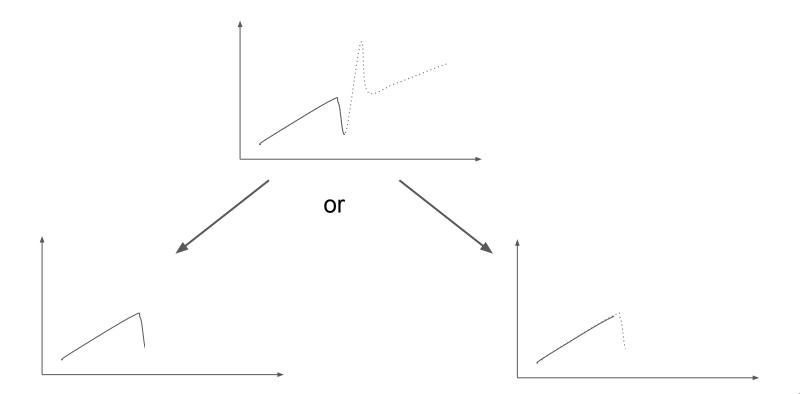
Pattern: Ingest time bucketing



- Bundle incoming events into datasets
 - Bucket on ingest / wall-clock time
 - Predictable bucketing, e.g. hour

- Sealed quickly at end of hour
- Mark dataset as complete
 - E.g. _SUCCESS flag

When data is late



Incompleteness recovery

```
class OrderShuffle(SparkSubmitTask):
    hour = DateHourParameter()
    delay_hours = IntParameter()
```

```
jar = 'orderpipeline.jar'
entry class = 'com.example.shop.OrderShuffleJob'
```

```
def requires(self):
    # Note: This delays processing by N hours.
    return [Order(hour=hour) for hour in
      [self.hour + timedelta(hour=h) for h in
      range(self.delay hours)]]
```

```
def output(self):
    return HdfsTarget("/prod/red/order/v1/"
    f"delay={self.delay}/"
    f"{self.hour:%Y/%m/%d/%H}/")
```

```
def app_options(self):
    return ["--hour", self.hour,
        "--delay-hours", self.delay_hours,
        "--order",
        ",".join([i.path for i in self.input()]),
        "--output", self.output().path]
```

```
val orderLateCounter = longAccumulator("order-event-late")
```

```
val hourPaths = conf.order.split(",")
val order = hourPaths
.map(spark.read.avro(_))
.reduce(a, b => a.union(b))
```

```
val orderThisHour = order
.map({ cl =>
    # Count the events that came after the delay window
    if (cl.eventTime.hour + config.delayHours <
        config.hour) {
        orderLateCounter.add(1)
    }
    order
})
.filter(cl => cl.eventTime.hour == config.hour)
```

Fast data, complete data

```
class OrderShuffleAll(WrapperTask):
    hour = DateHourParameter()
```

```
def requires(self):
    return [OrderShuffle(hour=self.hour, delay_hour=d)
        for d in [0, 4, 12]]
```

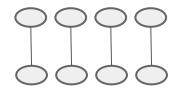
```
class OrderDashboard(mysql.CopyToTable):
    hour = DateHourParameter()
```

```
def requires(self):
    return OrderShuffle(hour=self.hour, delay hour=0)
```

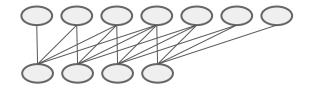
```
class FinancialReport(SparkSubmitTask):
    date = DateParameter()
```

```
def requires(self):
    return [OrderShuffle(
        hour=datetime.combine(self.date, time(hours=h)),
        delay_hour=12)
        for h in range(24)]
```

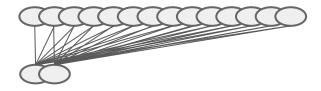
Delay: 0



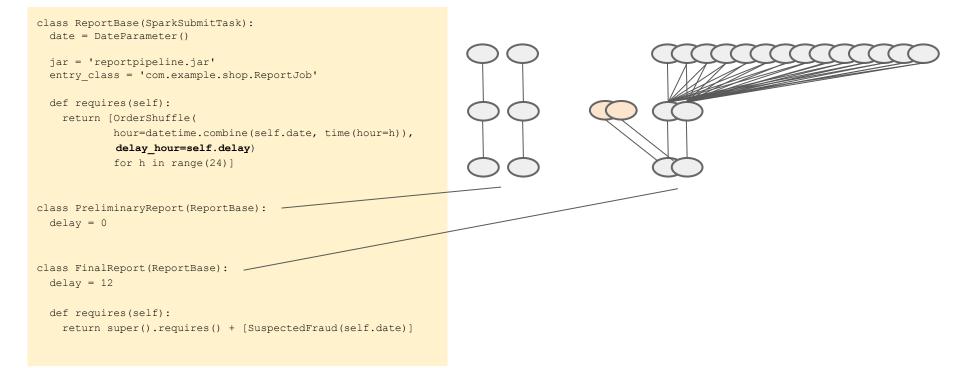
```
Delay: 4
```



Delay: 12



Lambda in batch



Human-delayed data

"These are my compensation claims for last January."

- Want: accurate reporting
- Want: current report status

Anti-pattern: Reprocessing

Dual time scopes

- What we knew about month X at date Y
- Deterministic
 - Can be backfilled, audited
- May require sparse dependency trees

```
class ClaimsReport(SparkSubmitTask):
    domain_month = MonthParameter()
    date = DateParameter()
```

```
jar = 'reportpipeline.jar'
entry_class = 'com.example.shop.ClaimsReportJob'
```

```
def requires(self):
    return [Claims(
        domain_month=self.domain_month,
        date=d)
        for date in date_range(
            self.domain_month + timedelta(month=1),
            self.date)]
```

Recursive dependencies

- Use yesterday's dataset + some delta
 - Starting point necessary
- Often convenient, but operational risk
 - Slow backfills
- Mitigation: recursive jumps
 - Depend on previous month + all previous days in this month

```
class StockAggregateJob(SparkSubmitTask):
    date = DateParameter()
```

```
jar = 'stockpipeline.jar'
entry_class = 'com.example.shop.StockAggregate'
```

def requires(self):
 yesterday = self.date - timedelta(days=1)
 previous = StockAggregateJob(date=yesterday)
 return [StockUpdate(date=self.date), previous]

Recursive dependency strides

- Mitigation: recursive strides
- y/m/1 depends on y/m-1/1
- Others depend on y/m/1 + all previous days in this month

```
class StockAggregateStrideJob(SparkSubmitTask):
    date = DateParameter()
```

```
jar = 'stockpipeline.jar'
entry_class = 'com.example.shop.StockAggregate'
```

```
def requires(self):
    first_in_month = self.date.replace(day=1)
    base = first_in_month - relativedelta(months=1) \
    if self.date.day == 1 else first_in_month
    return ([StockAggregateStrideJob(date=base)] +
        [StockUpdate(date=d) for d in
        rrule(freq=DAILY, dtstart=base, until=self.date)])
```

Business logic with history

Example: Forming sessions

- Valuable for
 - User insights
 - Product insights
 - A/B testing
 - o ...

• Sequence of clicks at most 5 minutes apart?

• In order to emit sessions in one hour, which hours of clicks are needed?

- Sequence of clicks at most 5 minutes apart?
- Maximum length 3 hours?

• In order to emit sessions in one hour, which hours of clicks are needed?

- Sequence of clicks at most 5 minutes apart.
- Maximum length 3 hours.

Examples, window = 5am - 9am:

- Clicks at [6:00, 6:01, 6:03, 6:45, 6:47]?
 - Two sessions, 3 and 2 minutes long.

- Sequence of clicks at most 5 minutes apart.
- Maximum length 3 hours.

Examples, window = 5am - 9am:

- Clicks at [6:00, 6:01, 6:03, 6:45, 6:47]?
 Two sessions, 3 and 2 minutes long.
- [5:00, 5:01, 5:03]?
 - One session, 3 minutes?

- Sequence of clicks at most 5 minutes apart.
- Maximum length 3 hours.

Examples, window = 5am - 9am:

- Clicks at [6:00, 6:01, 6:03, 6:45, 6:47]?
 - Two sessions, 3 and 2 minutes long.
- [5:00, 5:01, 5:03]?
 - One session, 3 minutes?
 - [(4:57), 5:00, 5:01, 5:03]?
 - [(2:01), (every 3 minutes), (4:57), 5:00, 5:01, 5:03]?

Occurrences with unbounded time spans

- E.g. sessions, behavioural patterns
- You often need a broader time range than expected
- You may need data from the future
- You may need infinite history
 - Recursive strides?
 - Introduce static limits, e.g. cut all sessions at midnight?
 - Emit counters to monitor assumptions.

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Secrets of valuable data engineering

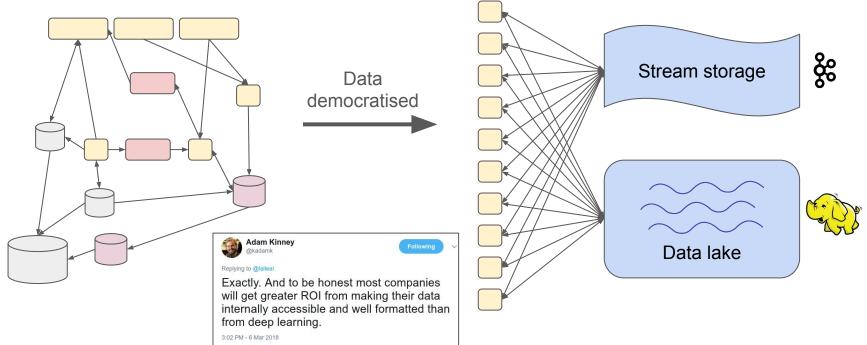
- 1. Avoid complexity and distributed systems
 - Your data fits in one machine.
- 2. Pick the slowest data integration you can live with
 - Batch >> streaming >> service.
 - \circ Slow data \rightarrow easy operations \rightarrow high innovation speed
- 3. Functional architectural principles
 - Pipelines
 - Immutability
 - Reproducibility
 - Idempotency
- 4. Master workflow orchestration

Team concurrency

- Pipelines
 - Parallel development without risk
- Immutability
 - Data reusability without risk
- Reproducibility, idempotency
 - Preserving immutability
 - Reduces operational risk
 - Stable experiments
- Workflow orchestration
 - Data handover between systems & teams
 - Reduces operational overhead

Data science reproducibility crisis!

The real value of big data



Resources, credits

Time libraries:

- Java: Joda time java.time
- Scala: chronoscala
- Python: dateutil, pendulum

Presentation on operational tradeoffs:

https://www.slideshare.net/lallea/data-ops-in-practice

Thank you,

- Konstantinos Chaidos, Spotify
- Lena Sundin, independent

Laptop sticker

Vintage data visualisations, by Karin Lind.

- Charles Minard: Napoleon's Russian campaign of 1812. Drawn 1869.
- Matthew F Maury: Wind and Current Chart of the North Atlantic. Drawn 1852.
- Florence Nightingale: Causes of Mortality in the Army of the East. Crimean war, 1854-1856. Drawn 1858.
 - Blue = disease, red = wounds, black = battle + other.
- Harold Craft: Radio Observations of the Pulse Profiles and Dispersion Measures of Twelve Pulsars, 1970
 - Joy Division: Unknown Pleasures, 1979
 - $\circ \quad \xrightarrow{\text{``Joy plot"}} \rightarrow \text{``ridge plot"}$

