
THE FUTURE IS NOW

Scalable Predictive Pipelines with Spark and Scala

Tom van der Weide
Based on a presentation from Dimitris Papadopoulos

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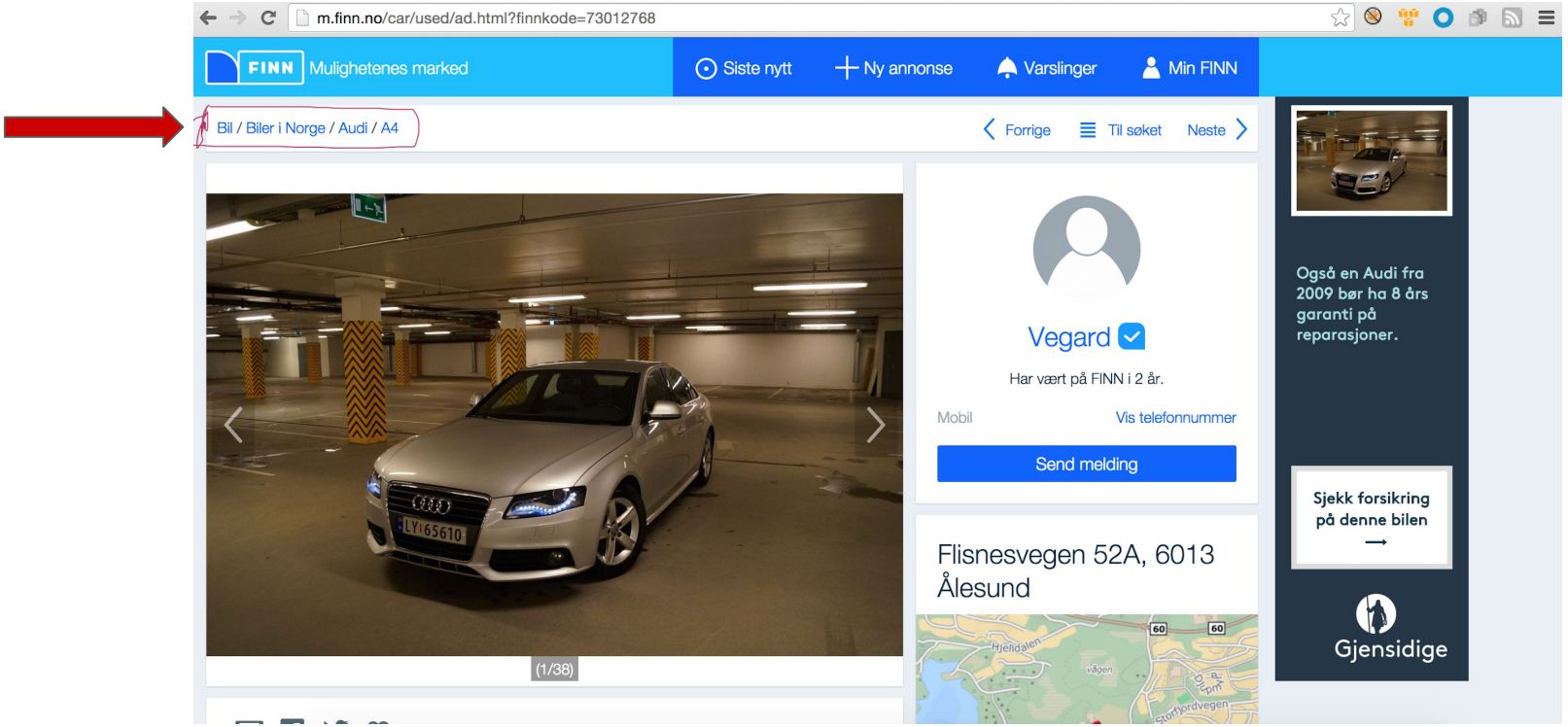
Event Tracking Data



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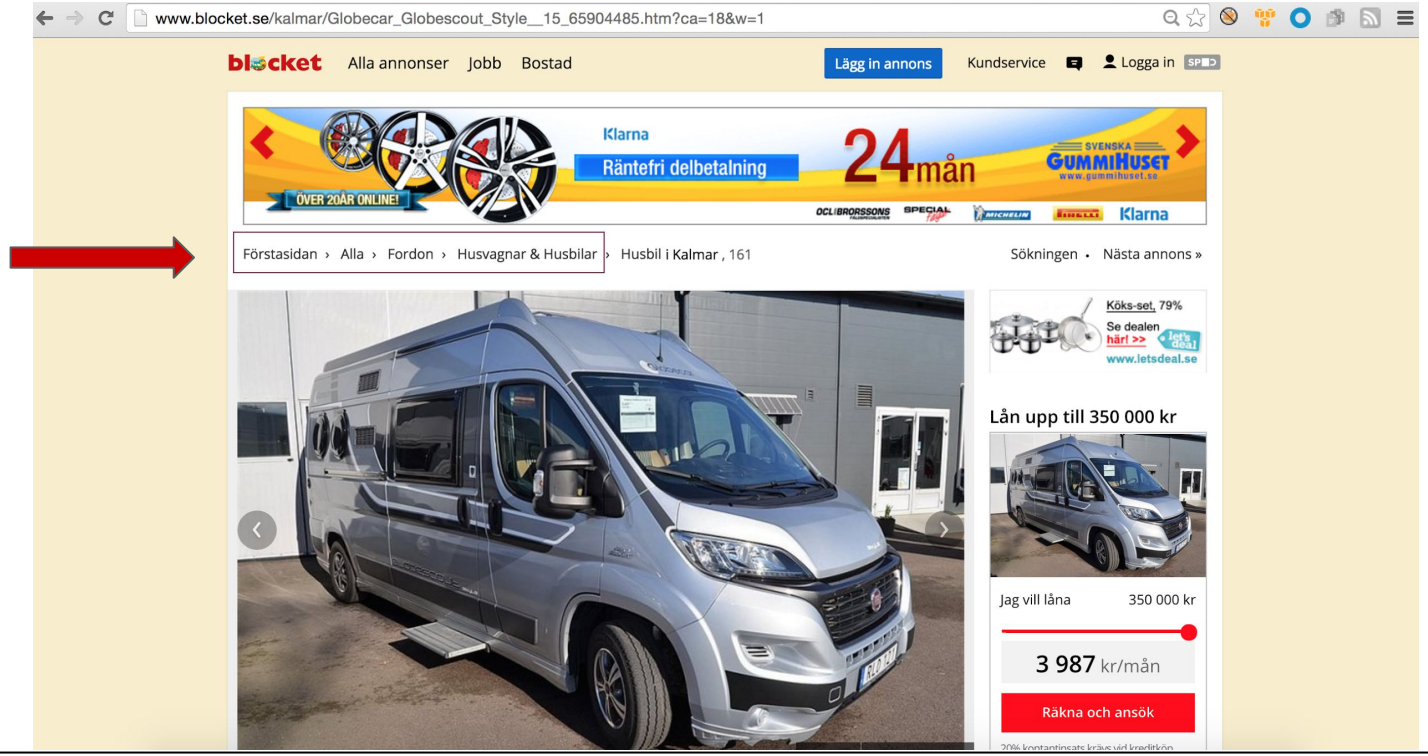

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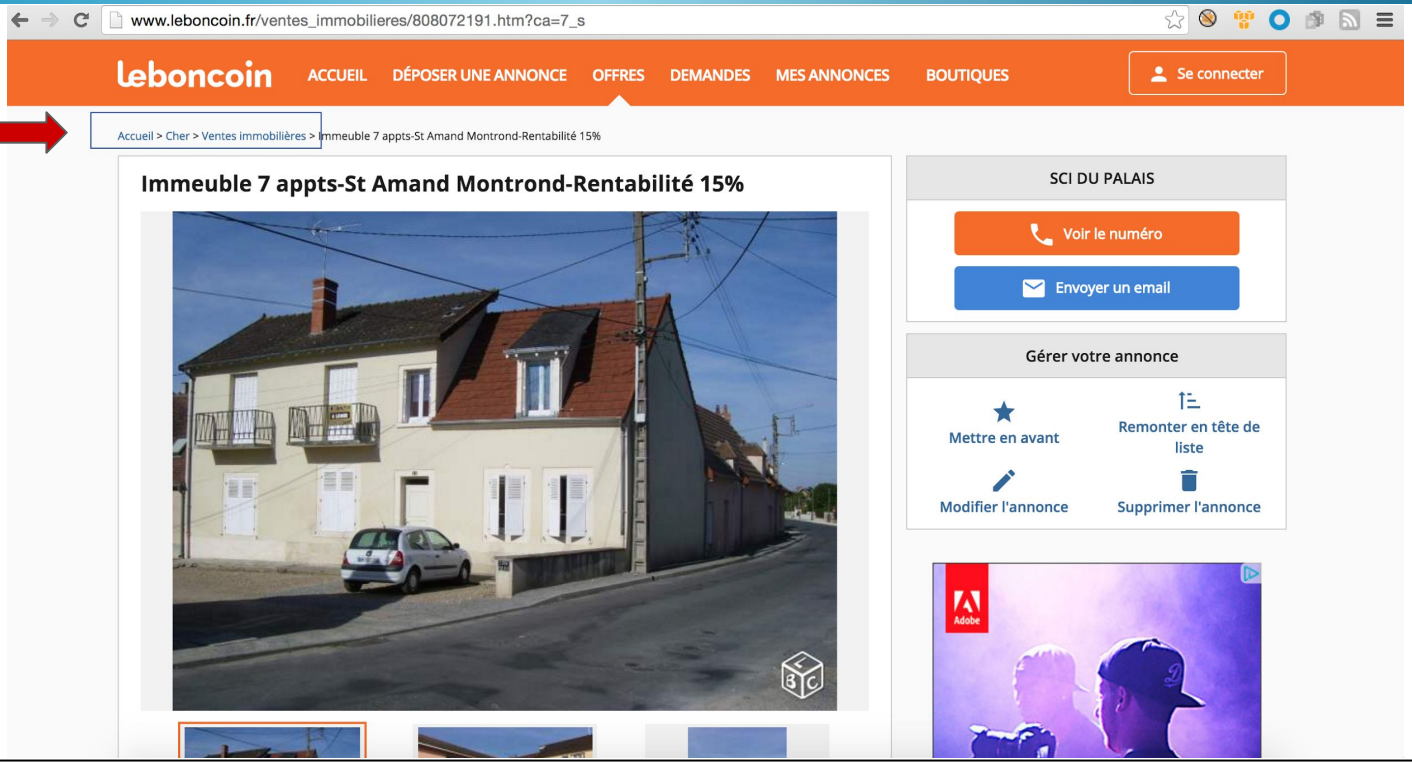

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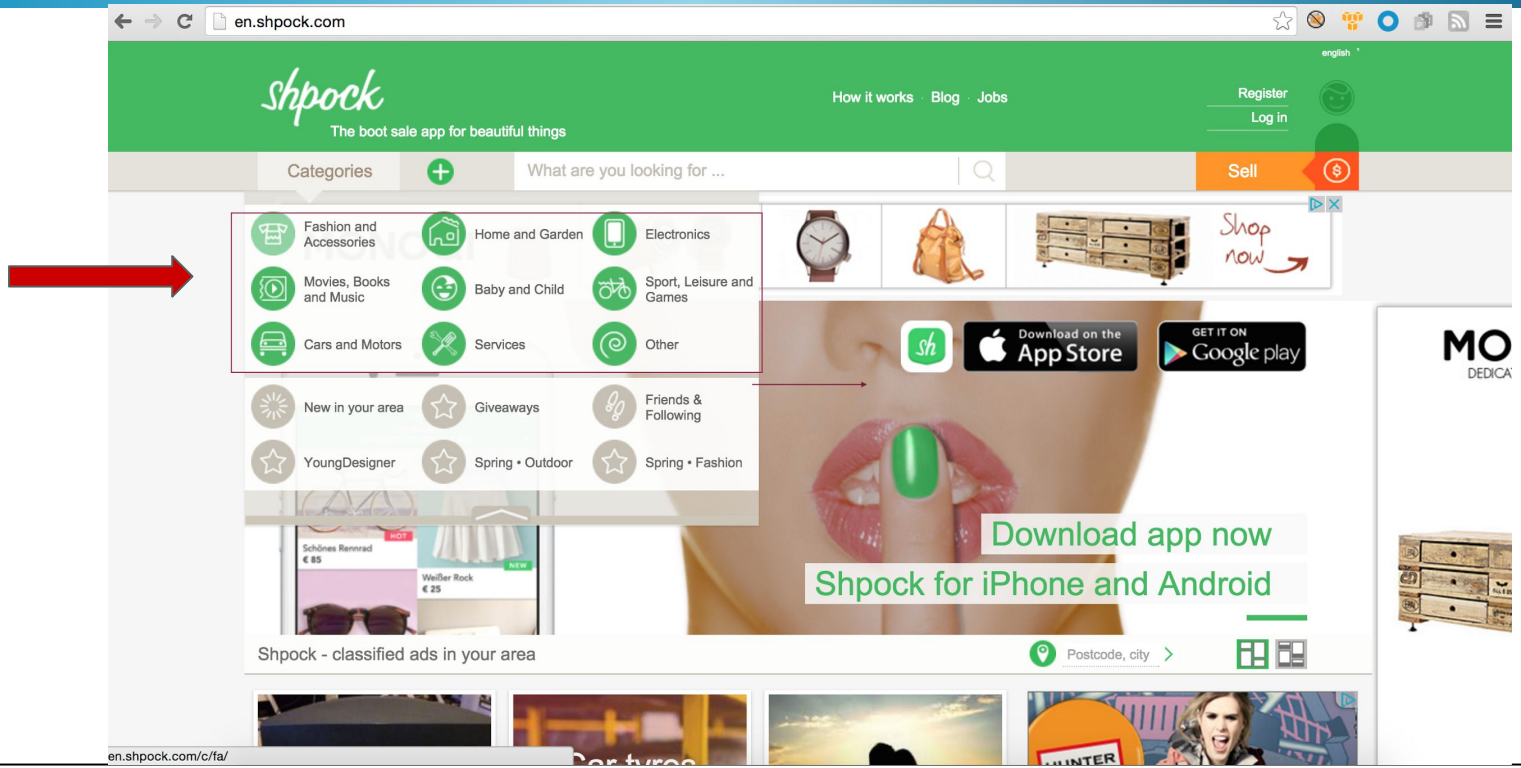
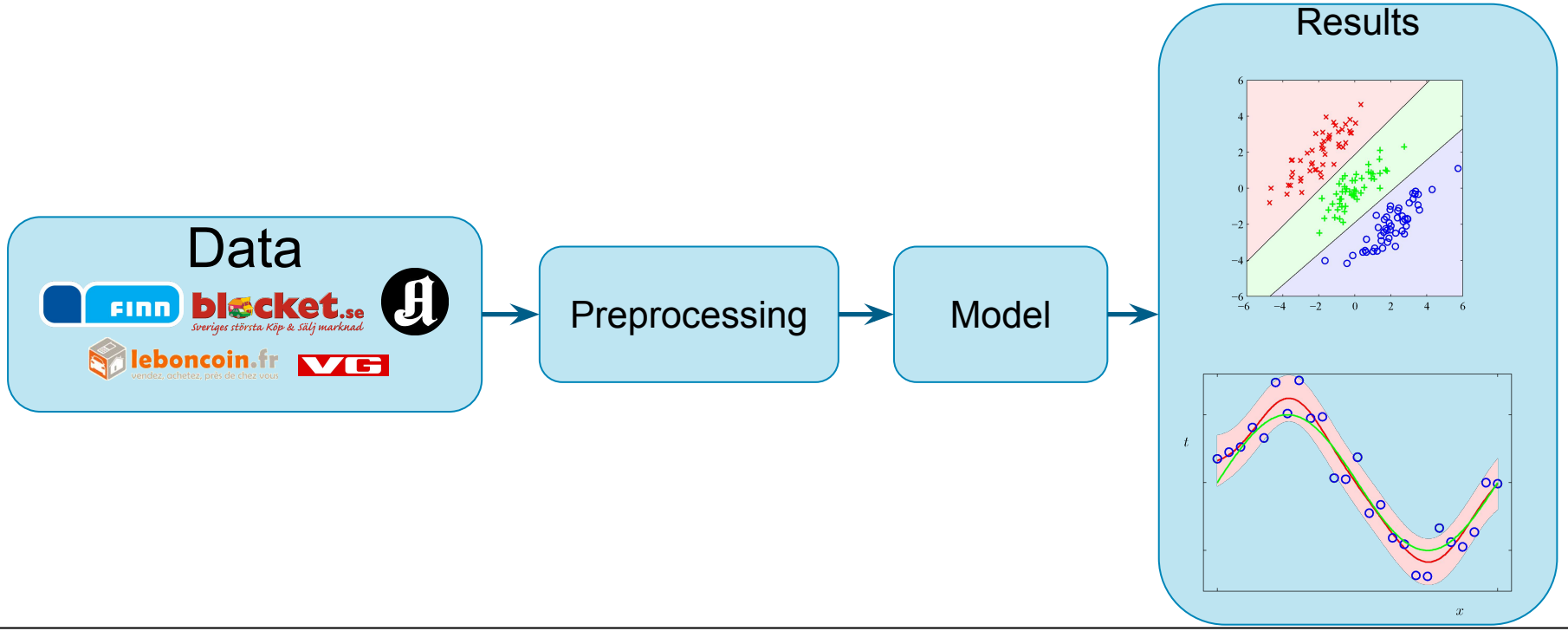


Data Science Tasks

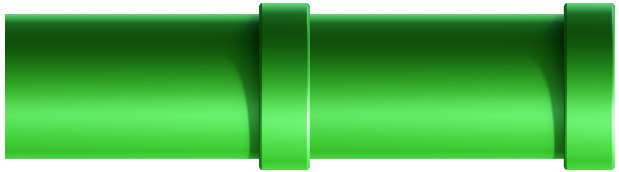


Outline

1. Using Spark ML Pipelines

2. Scalable Pipelines

Pipeline



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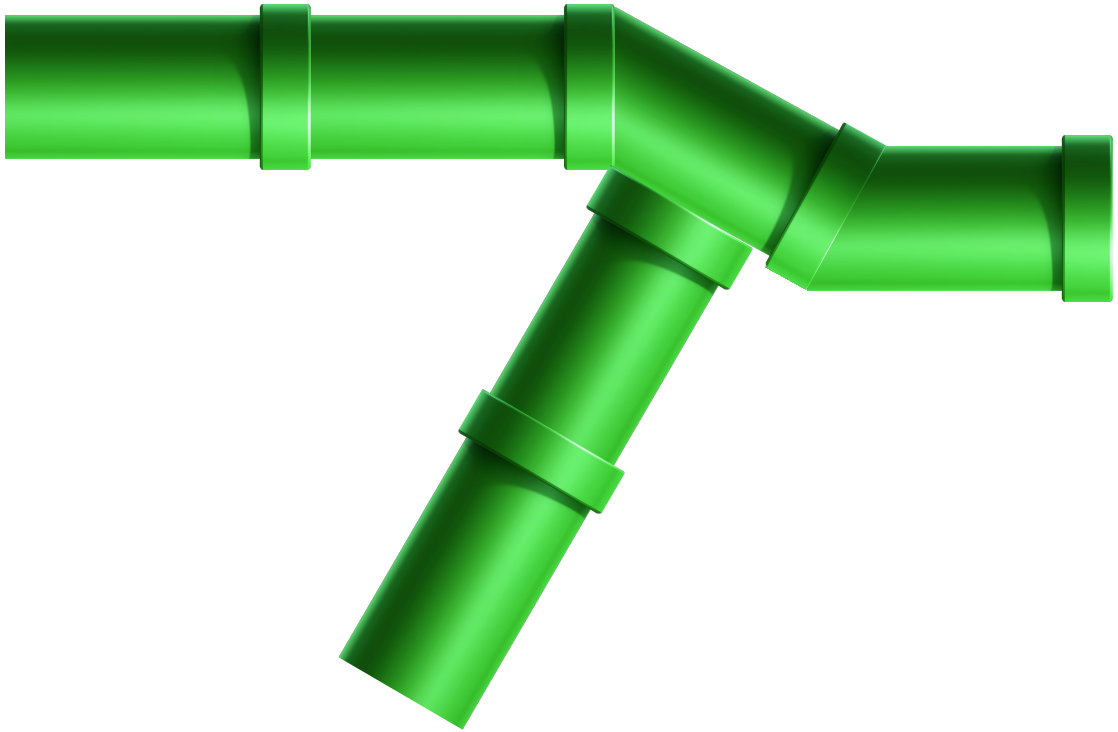

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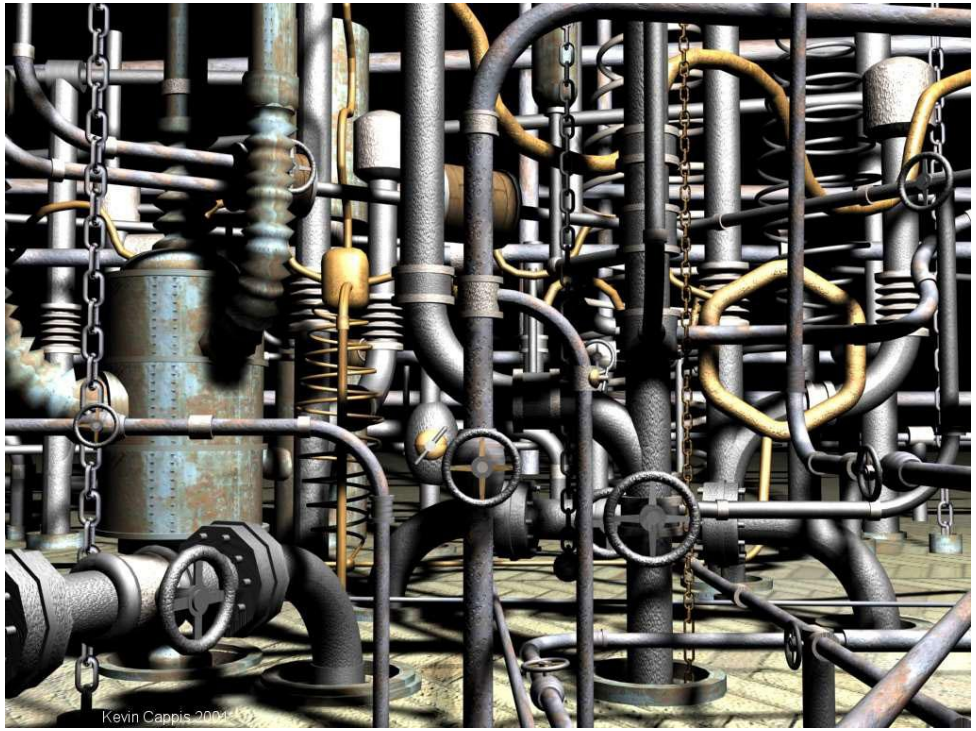

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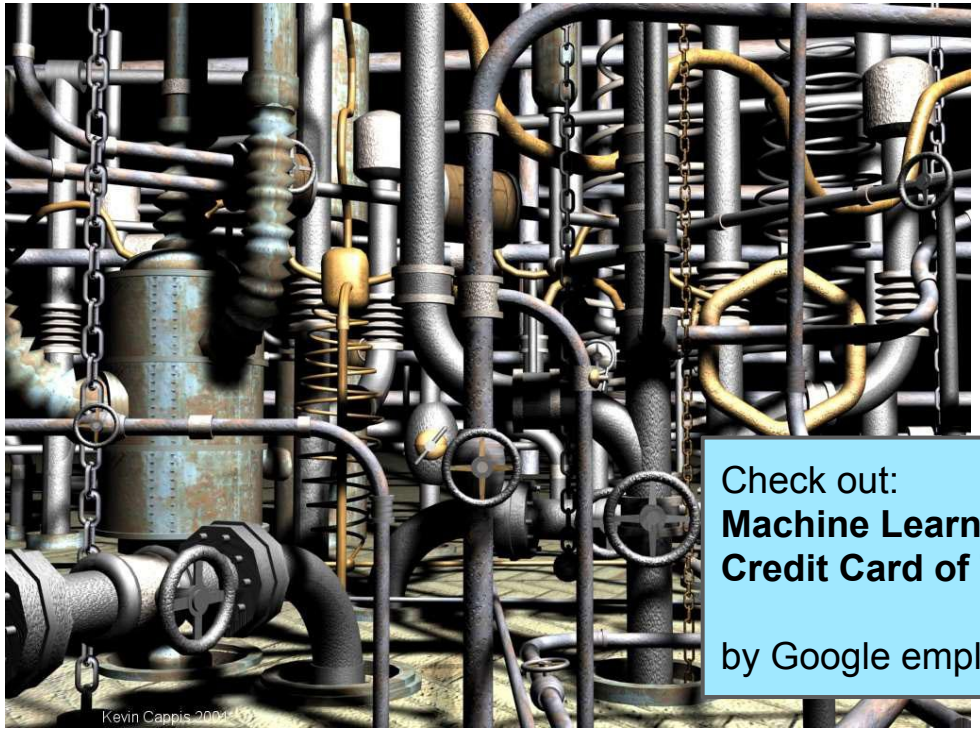


Check out:
Machine Learning: The High-Interest Credit Card of Technical Debt

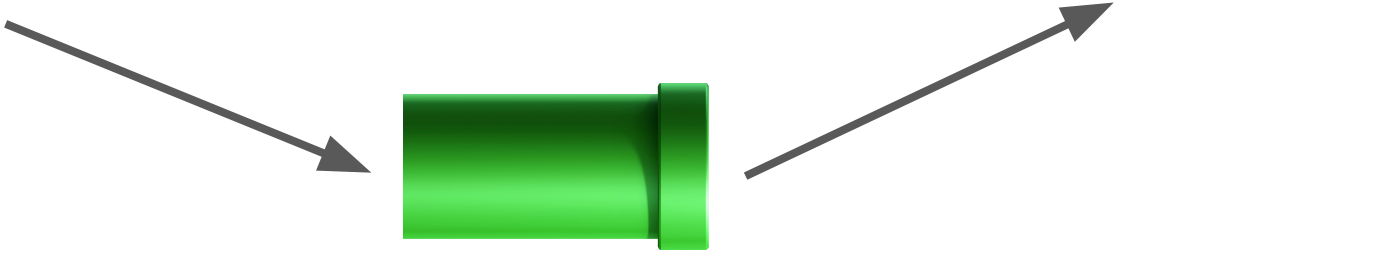
by Google employees

Not a pipe

Pipeline Stage

One or more inputs

Strictly one output



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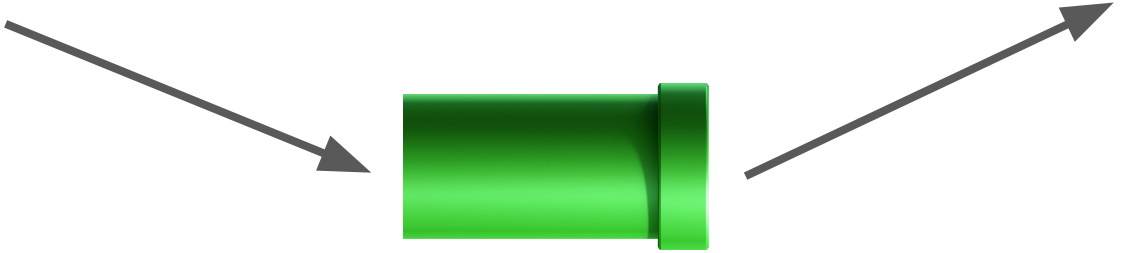

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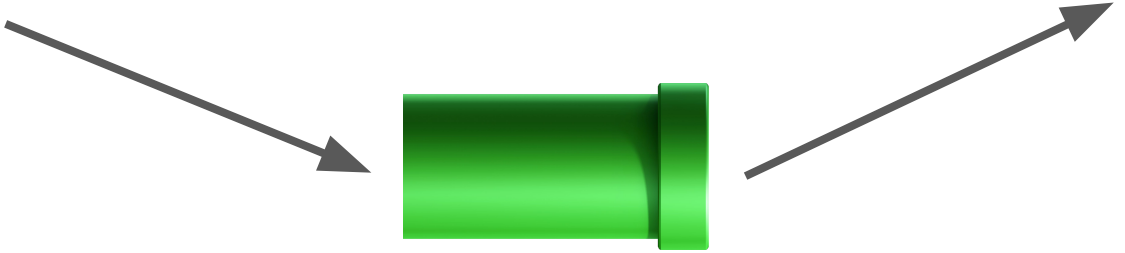
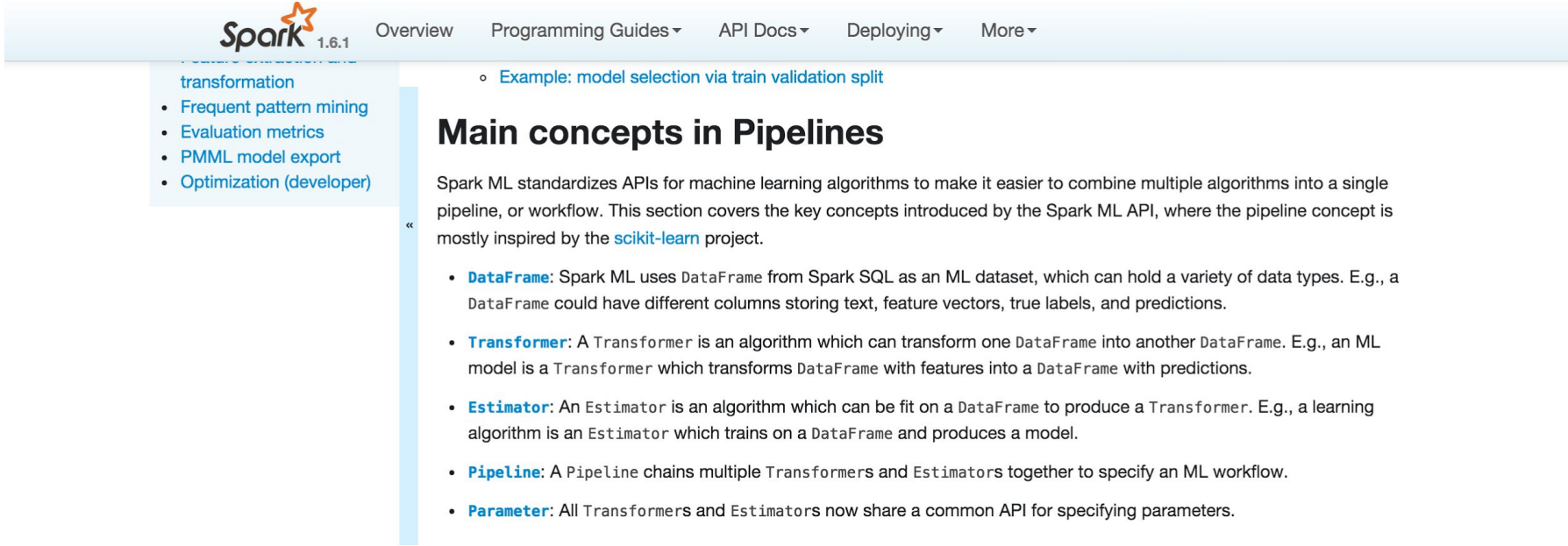


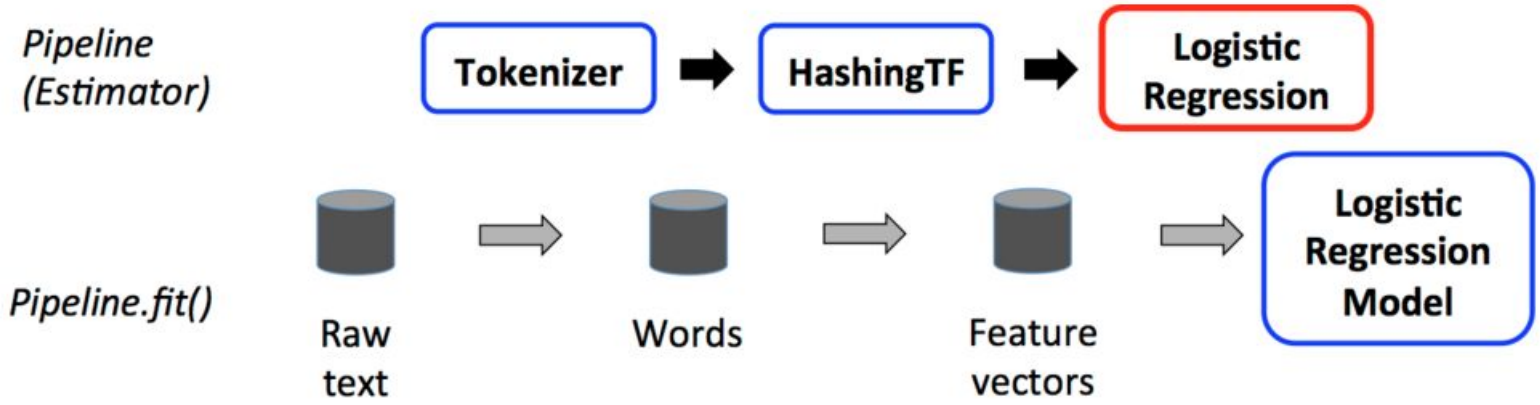
- Closed under concatenation
- Standalone and runnable
- Spark™ ML inside

Spark ML Pipelines



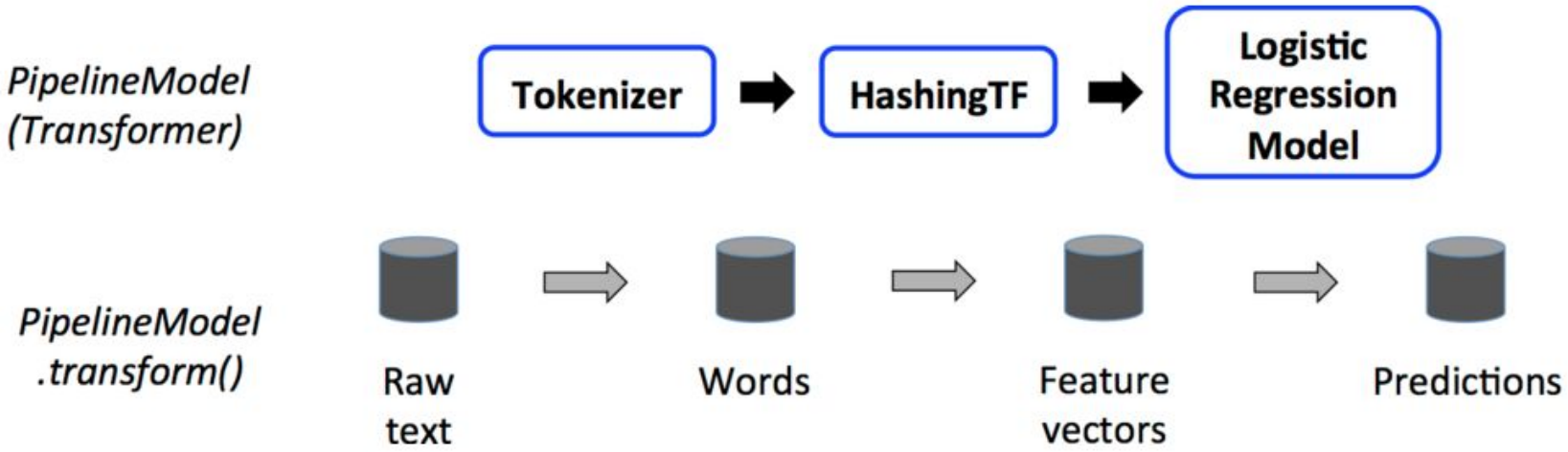
Spark ML Pipelines

Using a Pipeline to train a model

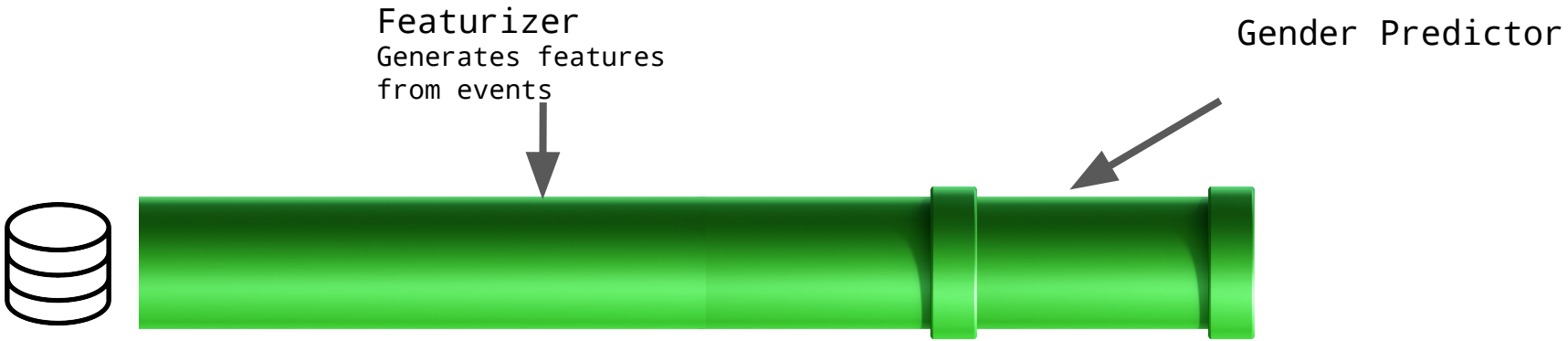


Spark ML Pipelines

Using a PipelineModel to get predictions



Example: Gender Prediction Pipeline



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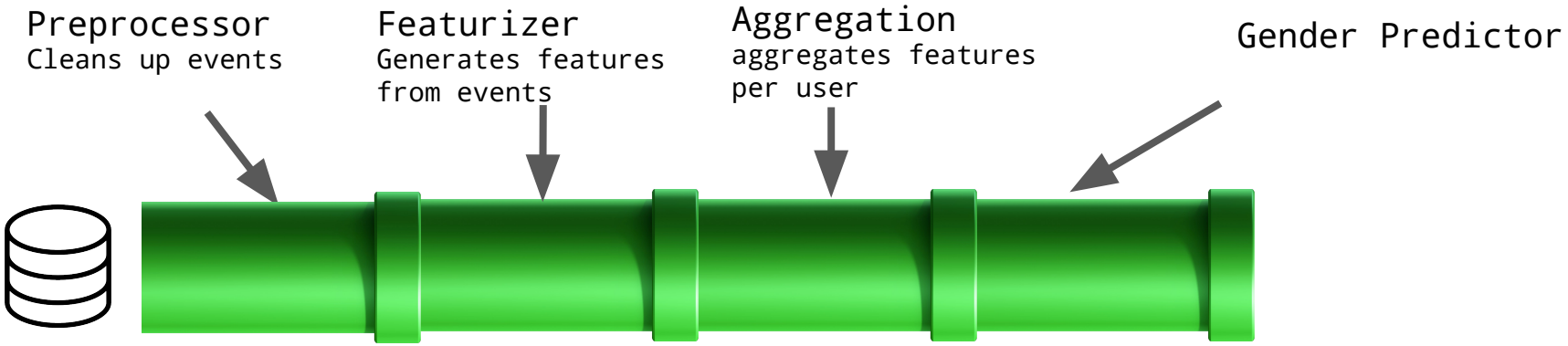

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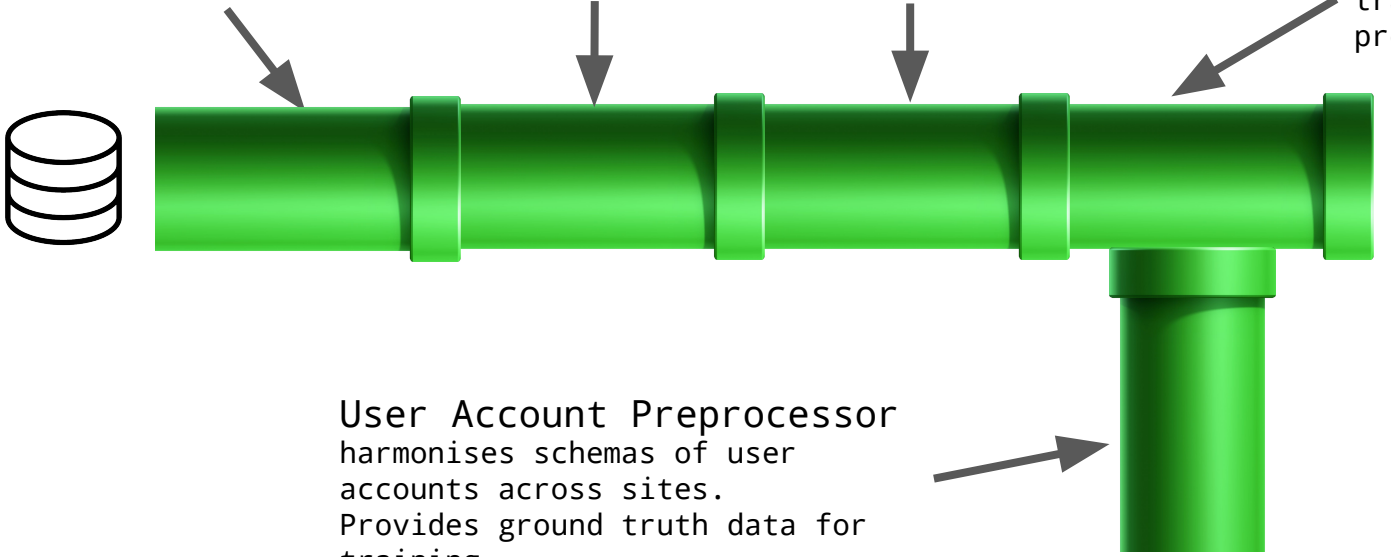
Cleans up events

Featurizer
Generates features from events

Aggregation
aggregates features per user

Gender Predictor
Joins features with users, trains classifier & computes predictions



User Account Preprocessor
harmonises schemas of user accounts across sites.
Provides ground truth data for training.

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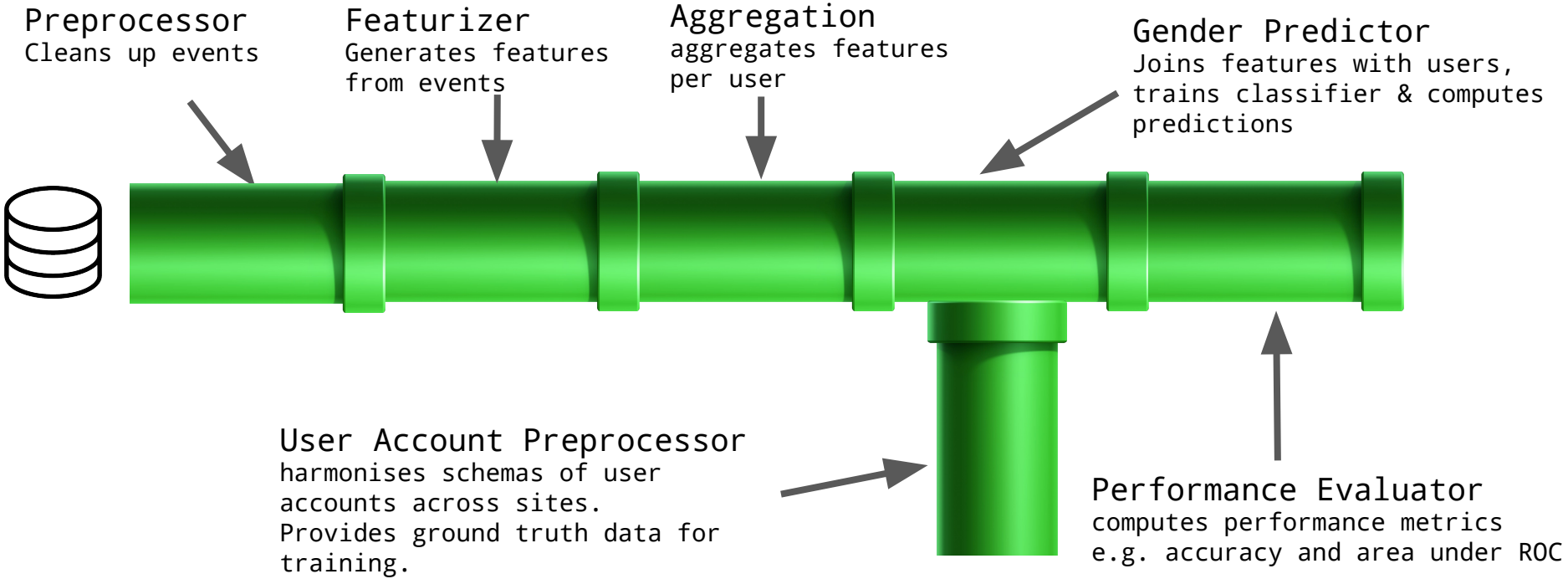
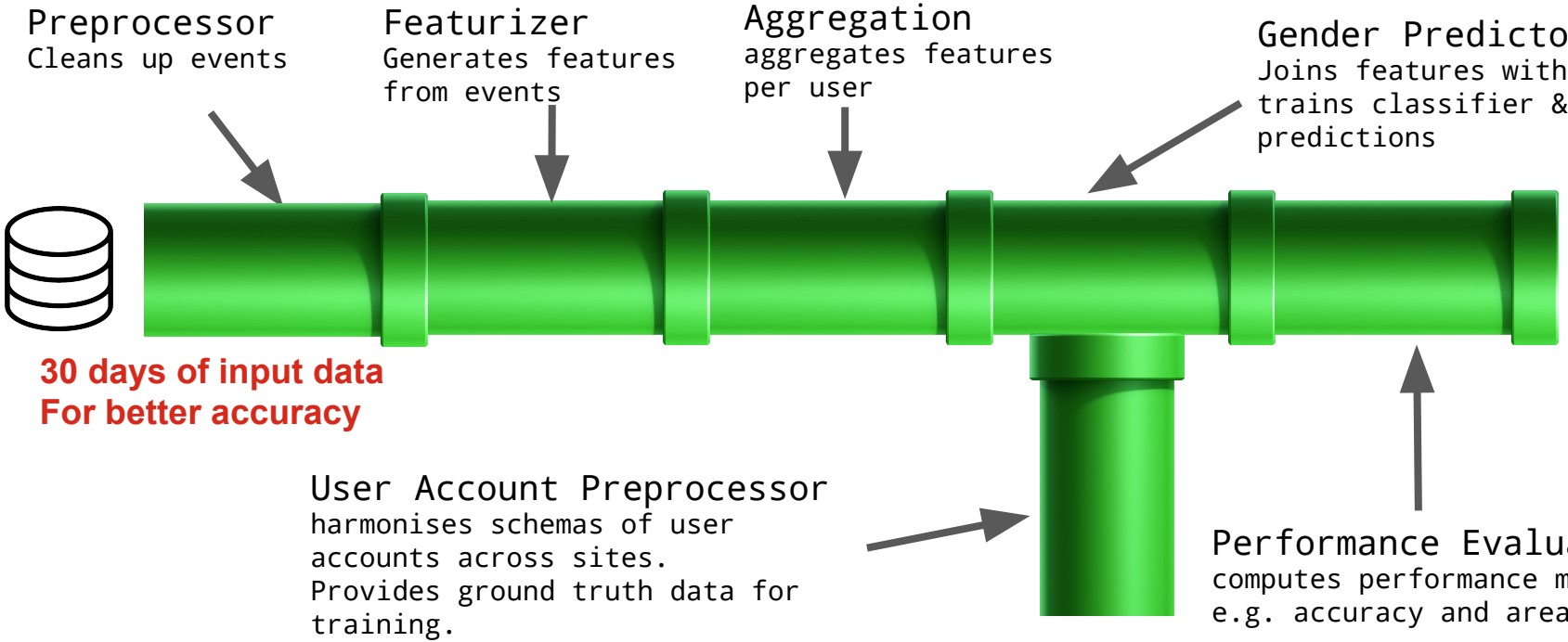
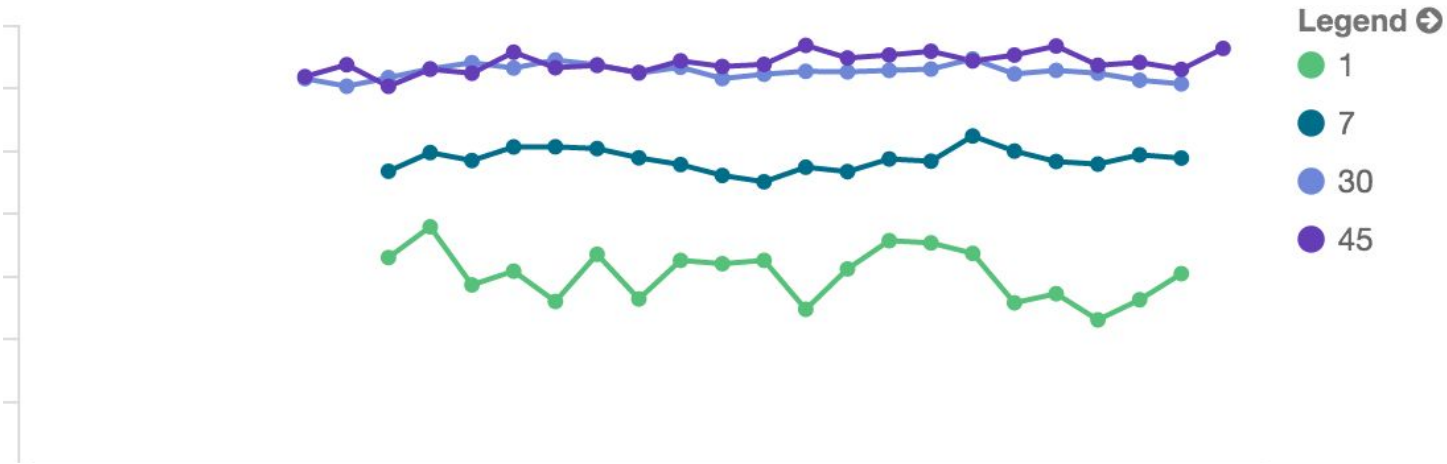


Scalability pain points

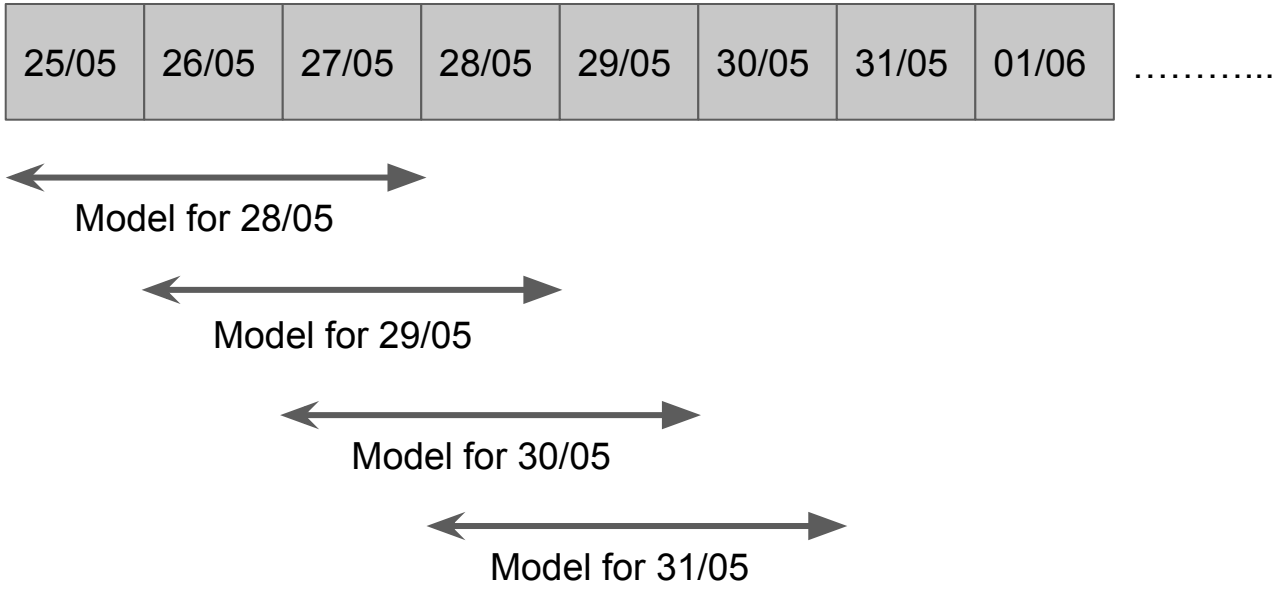


More data for better performance



Redundant processing

Input data per day



Scalable Pipelines: pain points

"What will happen if we try to process
*30 days worth of data (e.g. **6B events**) ???"*

Memory and processing heavy

- In one use-case, for 7 days lookback (~7 x 200M events)
  we used to need 20 Spark executors with 22G of memory each.

Not easily scalable

- As the lookback increases
- As more and more sites are incorporated into our pipelines

Redundant processing

- For K days of lookback, we are repeating processing of K-1 days worth of data,
  when we run the pipeline every day, in a rolling window fashion.

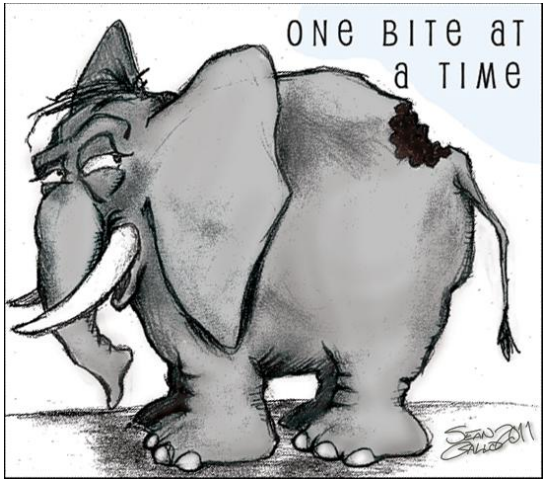
Saved by Algebra

- The operations (*op*) along with the corresponding data structures (S) that we are interested in are ***monoids***.
  - Associative:
    - for all A,B,C in S, (A *op* B) *op* C = A *op* (B *op* C)
  - Identity element:
    - there exists E in S such that for each A in S, E *op* A = A *op* E = A
- Examples:
  - Summation: 1 + 2 + 3 + 4 = (1 + 2) + (3 + 4) = 1 + ((2 + 3) + 4)
  - String array concatenation: [“foo”] + [“bar”] + [“baz”] = [“foo”, “bar”] + [“baz”]

Scalable Pipelines: in monoids fashion

Split work into smaller chunks, cache intermediate results

- Split the aggregations into smaller chunks
  - Persist aggregations per day
- Combine partial aggregations into final feature vectors



Scalable Pipelines: building blocks

User Defined Functions (UDF)

compute a value looking at a single row

e.g. SELECT **concat**('user', user_id) FROM events

User Defined **Aggregate** Functions (UDAF) since Spark 1.5

computation over groups of rows

e.g. SELECT user_id, **AVG**(time_spent) FROM events **GROUP BY** user_id

Example: map with term frequencies

For some user, we already aggregated events per day:

```
val day1 = Map("cars" -> 2.0, "kitchen" -> 1.0, "house" -> 3.0)
val day2 = Map("kitchen" -> 4.0, "house" -> 1.0, "furniture" -> 5.0)
```

Monoid operation: MapAggregator ⊕

i.e. m1 ⊕ m2 ⊕ m3 = (m1 ⊕ m2) ⊕ m3 = m1 ⊕ (m2 ⊕ m3)

m0 = Map()

Result:

```
val together = Map("cars" -> 2.0, "kitchen" -> 5.0, "house" -> 4.0, "furniture" -> 5.0)
```

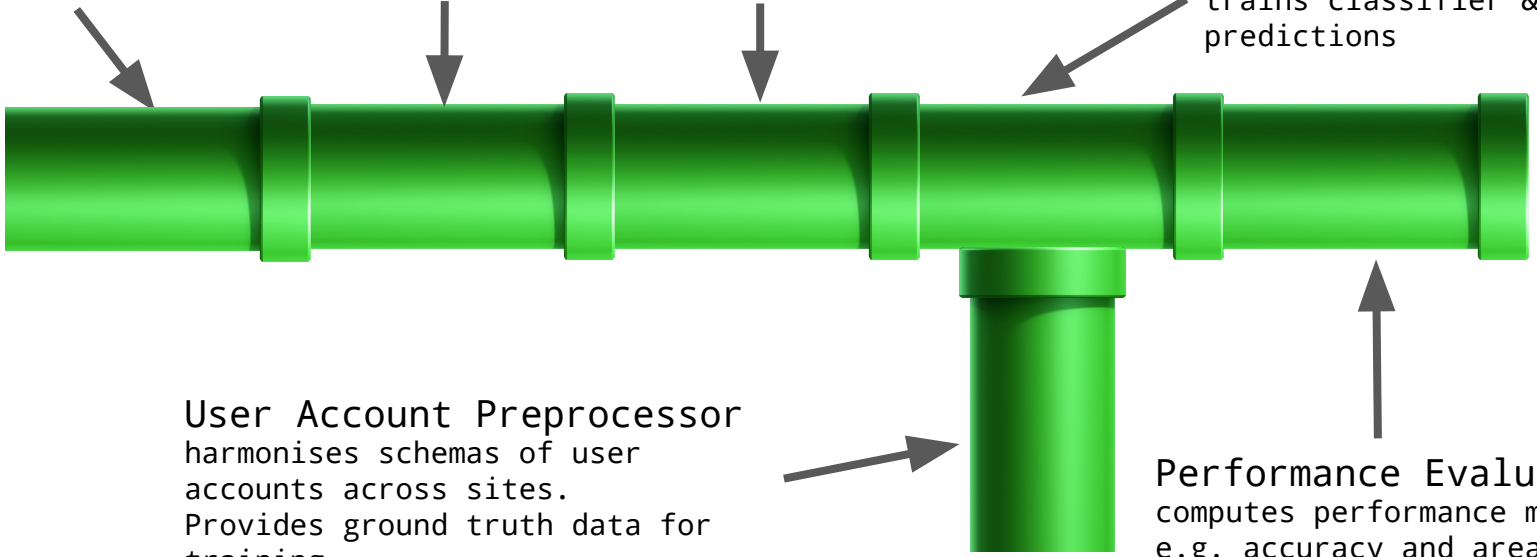
```scala
object MapAggregator extends UserDefinedAggregateFunction {
  type K = String
  type V = Double

  override def initialize(buffer: MutableAggregationBuffer): Unit =
    buffer.update(0, new HashMap[K, V])

  override def update(buffer: MutableAggregationBuffer, input: Row): Unit = {
    if (!input.isNullAt(0)) {
      buffer.update(0, sum(evaluate(buffer), evaluate(input)))
    }
  }

  override def merge(buffer1: MutableAggregationBuffer, buffer2: Row): Unit =
    buffer1.update(0, sum(evaluate(buffer1), evaluate(buffer2)))

  override def evaluate(buffer: Row): Map[K, V] =
    buffer.getAs[Map[K, V]](0)

  private def sum(map1: Map[K, V], map2: Map[K, V]): Map[K, V] =
    map1 ++ (for ((k, v) <- map2) yield k -> (v + map1.getOrElse(k, 0.0)))

  override def dataType = DataTypes.createMapType(StringType, DoubleType, true)
  override def inputSchema = new StructType().add("input", dataType)
  override def bufferSchema = new StructType().add("input", dataType)
  override def deterministic = true
}
```

Buffer for intermediate results

Merge buffers of two executors

Get content from buffer

Aggregation pipeline stage



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User Account Preprocessor
harmonises schemas of user accounts across sites.
Provides ground truth data for training.

Performance Evaluator
computes performance metrics e.g. accuracy and area under ROC

Scalable Pipelines: Aggregating Events

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class EventAggregator(override val uid: String) extends Transformer {

  def this() = this(Identifiable.randomUID("eventAggregator"))

  override def transform(dataset: DataFrame): DataFrame = {
    val aggregates = dataset.schema.fields
      .map { field: StructField => field.dataType match {
        case ArrayType(StringType, _) => concat_array_string(col(field.name)).as(field.name)
        case IntegerType | LongType | ShortType | FloatType | DoubleType => sum(col(field.name)).as(field.name)
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        case MapType(StringType, DoubleType, _) => MapAggregator(col(field.name)).as(field.name)
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      }
    }

    dataset.groupBy(col(userId), col(isAnonymous))
      .agg(aggregates.head, aggregates.tail: _*)
  }

  override def transformSchema(schema: StructType): StructType = schema

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Aggregating maps of feature frequency counts

Scalable Pipelines: closing remarks

- With User Defined Aggregate Functions, we have reduced the workload of our pipelines by a factor of 20!

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- Obvious gains: freeing up resources that can be used for running even more pipelines, faster, over even more input data

Scalable Pipelines: closing remarks

- Needless to say, more factors contribute towards a scalable pipeline:
  - Performance tuning of the Spark cluster
  - Use of a workflow manager (e.g. Luigi) for pipeline orchestration

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- But each one of these is a topic for a separate talk

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Q/A

Thank you!