Building a Scalable Recommender System with Apache Spark, Apache Kafka and Elasticsearch

Nick Pentreath

Nov / 14 / 16

About

- *@MLnick*
- Principal Engineer, IBM
- Apache Spark PMC
- Focused on machine learning
- Author of *Machine Learning with Spark*

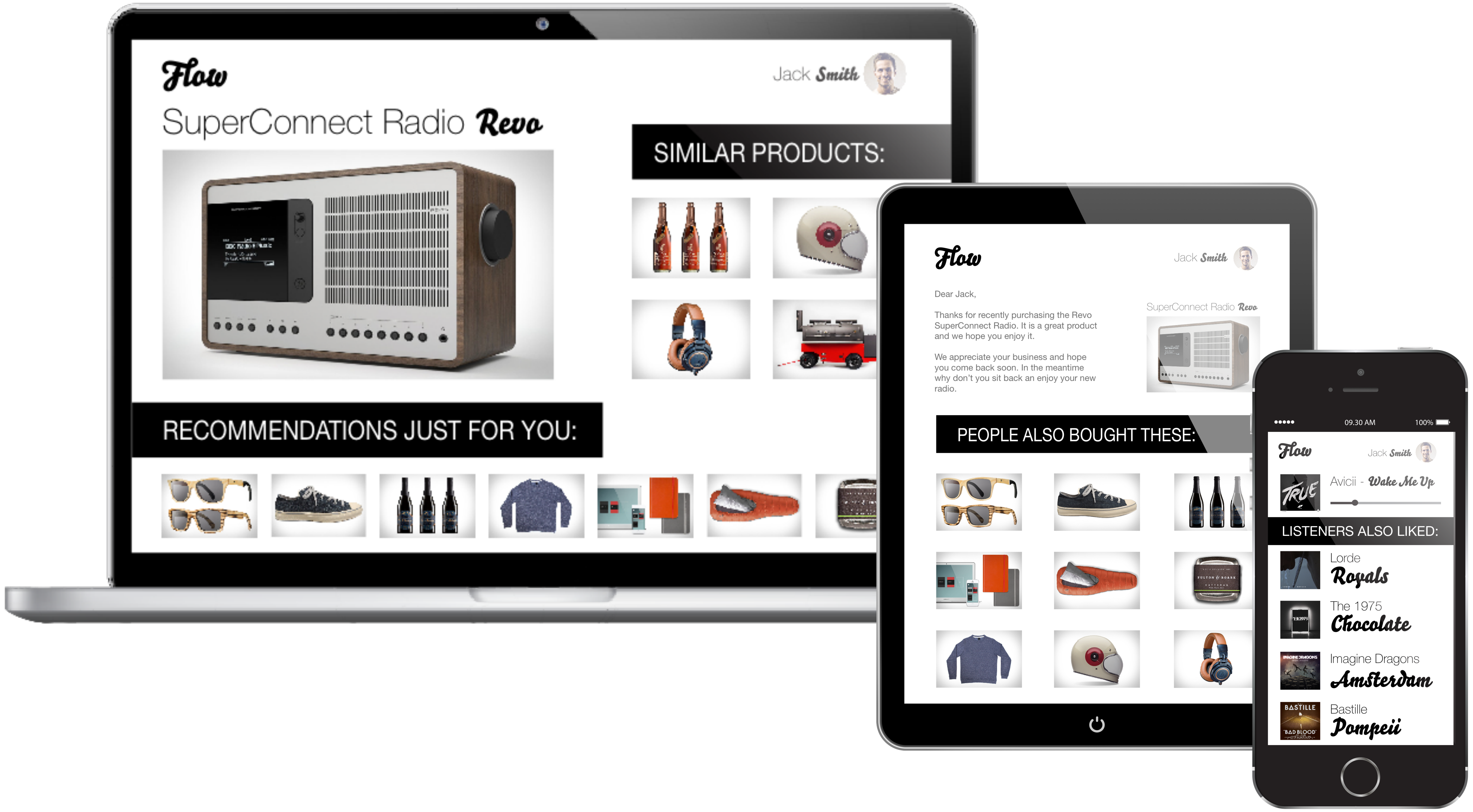
Agenda

- Recommender systems & the machine learning workflow
- Data modelling for recommender systems
- Why Spark, Kafka & Elasticsearch?
- Kafka & Spark Streaming
- Spark ML for collaborative filtering
- Deploying & scoring recommender models with Elasticsearch
- Monitoring, feedback & re-training
- Scaling model serving
- Demo

Recommender Systems & the ML Workflow

Recommender Systems

Overview

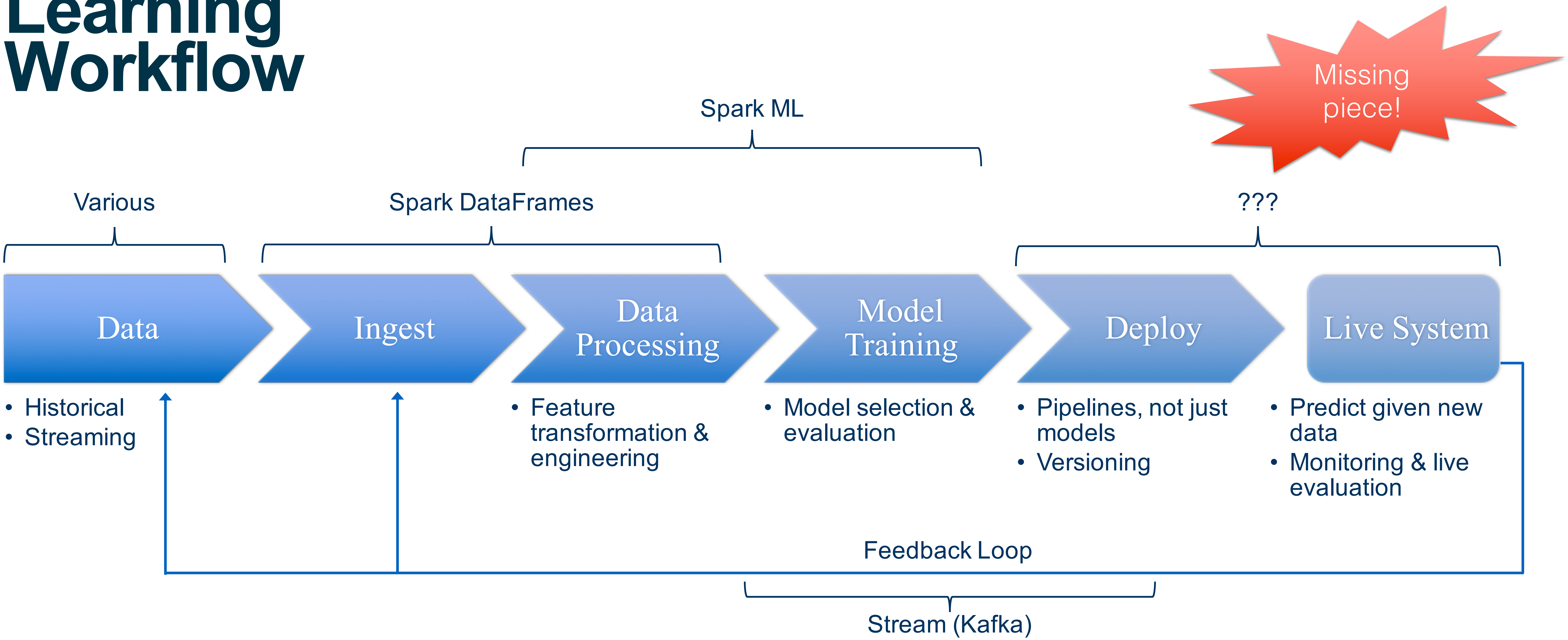


The Machine Learning Workflow

Perception

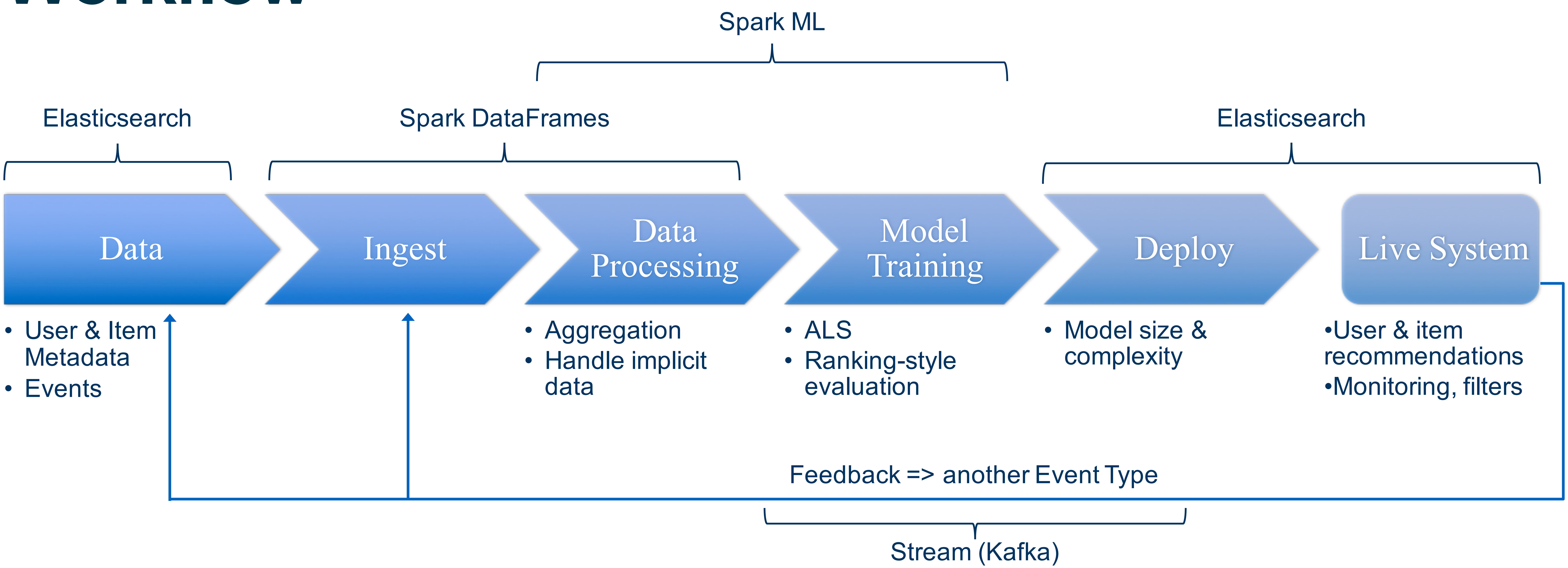
The Machine Learning Workflow

Reality



The Machine Learning Workflow

Recommender Version



Data Modeling for Recommender Systems

User and Item Metadata

Data model


```
{
  "user_id": "1",
  "name": "Joe Bloggs",
  "created_date": 1476884080,
  "updated_date": 1476946916,
  "last_active_date": 1476946962,
  "age": 32,
  "country": "Spain",
  "city": "Seville",
  ...
}
```

```
{
  "item_id": "10",
  "name": "LOL Cats",
  "description": "catscatscats",
  "category": ["Cat Videos", "Humour", "Animals"],
  "tags": ["cat", "lol", "funny", "cats", "felines"],
  "created_date": 1476884080,
  "updated_date": 1476884080,
  "last_played_date": 1476946962,
  "likes": 100000,
  "author_id": "321",
  "author_name": "ilikecats",
  "channel_id": "CatVideoCentral",
  ...
}
```

User and Item Metadata

System Requirements

Filtering & Grouping

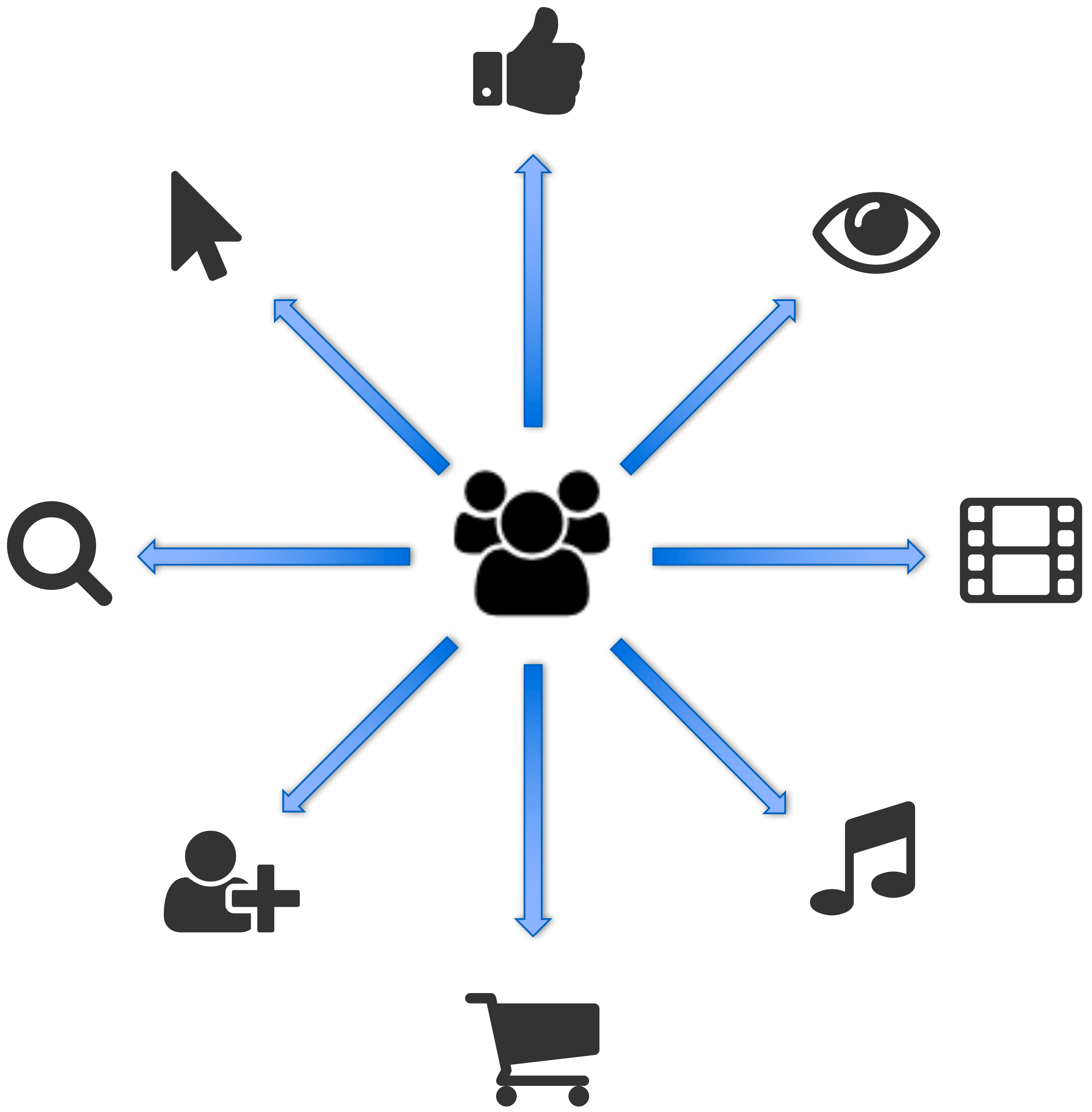
```
{
  "user_id": "1",
  "name": "Joe Bloggs",
  "created_date": 1476884080,
  "updated_date": 1476946916,
  "last_active_date": 1476946962,
  "age": 32,
  "country": "Spain",
  "city": "Seville",
  ...
}
```

Business Rules

```
{
  "item_id": "10",
  "name": "LOL Cats",
  "description": "catscatscats",
  "category": ["Cat Videos", "Humour", "Animals"],
  "tags": ["cat", "lol", "funny", "cats", "felines"],
  "created_date": 1476884080,
  "updated_date": 1476884080,
  "last_played_date": 1476946962,
  "likes": 100000,
  "author_id": "321",
  "author_name": "ilikecats",
  "channel_id": "CatVideoCentral",
  ...
}
```

Anatomy of a User Event

User Interactions



Implicit preference data

- Page view
- eCommerce - cart, purchase
- Media – preview, watch, listen

Intent data

- Search query

Explicit preference data

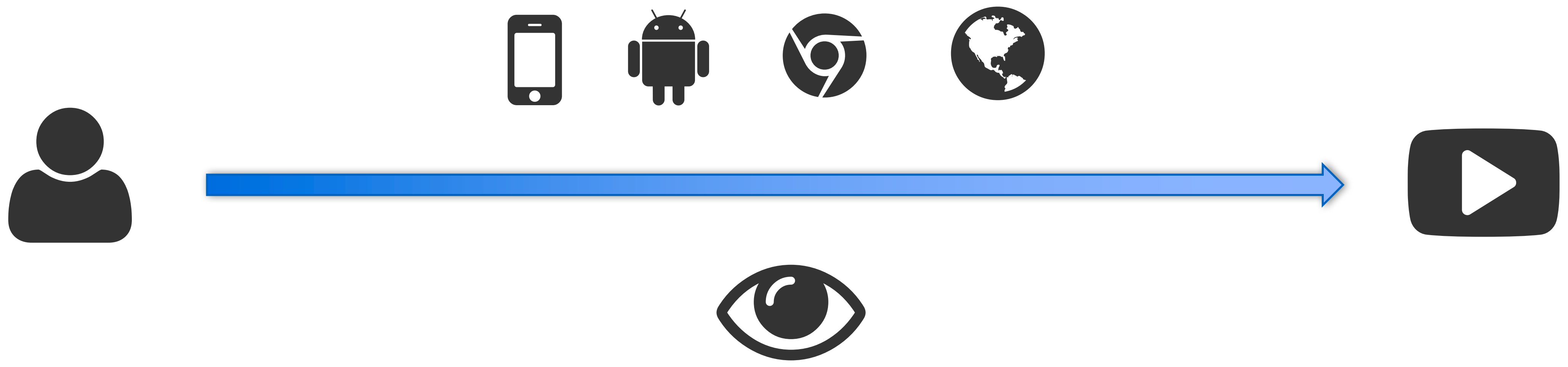
- Rating
- Review

Social network interactions

- Like
- Share
- Follow

Anatomy of a User Event

Data model




```
{
  "user_id": "1",
  "item_id": "10",
  "event_type": "page_view",
  "timestamp": 1476884080,
  "referrer": "http://spark.tc",
  "ip": "123.12.12.12",
  "device_type": "Smartphone",
  "user_agent_os": "Android",
  "user_agent_type": "Mobile Browser",
  "user_agent_family": "Chrome Mobile",
  "geo":"50.8503, 4.3517"
  ...
}
```

Anatomy of a User Event

How to handle implicit feedback?


```
{
  "user_id": "1",
  "item_id": "10",
  "event_type": "page_view",
  "weight": 1.0,
  "timestamp": 1476884080,
  "referrer": "http://spark.tc",
  "ip": "123.12.12.12",
  "device_type": "Smartphone",
  "user_agent_os": "Android",
  "user_agent_type": "Mobile Browser",
  "user_agent_family": "Chrome Mobile",
  "geo":"50.8503, 4.3517"
  ...
}
```

Why Kafka, Spark & Elasticsearch?

Why Kafka?

Scalability

- De facto standard for a *centralized enterprise message / event queue*

Integration

- Integrates with just about every storage & processing system
- Good Spark Streaming integration – *1st class citizen*
- Including for Structured Streaming (but still very new & rough!)

Why Spark?

DataFrames

- Events & metadata are “lightly structured” data
- Suited to DataFrames
- Pluggable external data source support

Spark ML

- Spark ML pipelines – including scalable ALS model for collaborative filtering
- Implicit feedback & NMF in ALS
- Cross-validation
- Custom transformers & algorithms

Why Elasticsearch?

Storage

- Native JSON
- Scalable
- Good support for time-series / event data
- Kibana for data visualisation
- Integration with Spark DataFrames

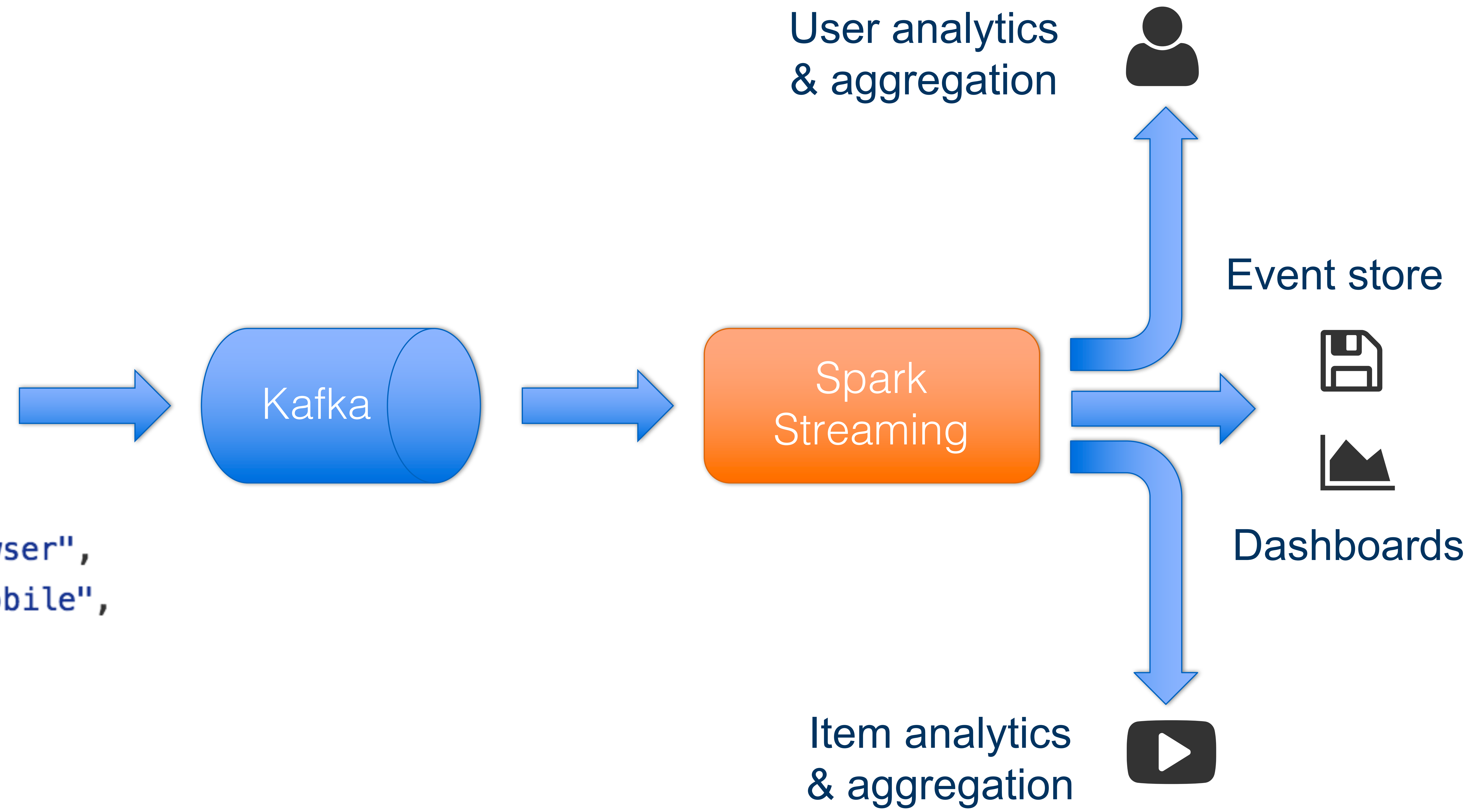
Scoring

- Full-text search
- Filtering
- Aggregations (grouping)
- Search ~== recommendation (more later)

Kafka for Recommender Systems

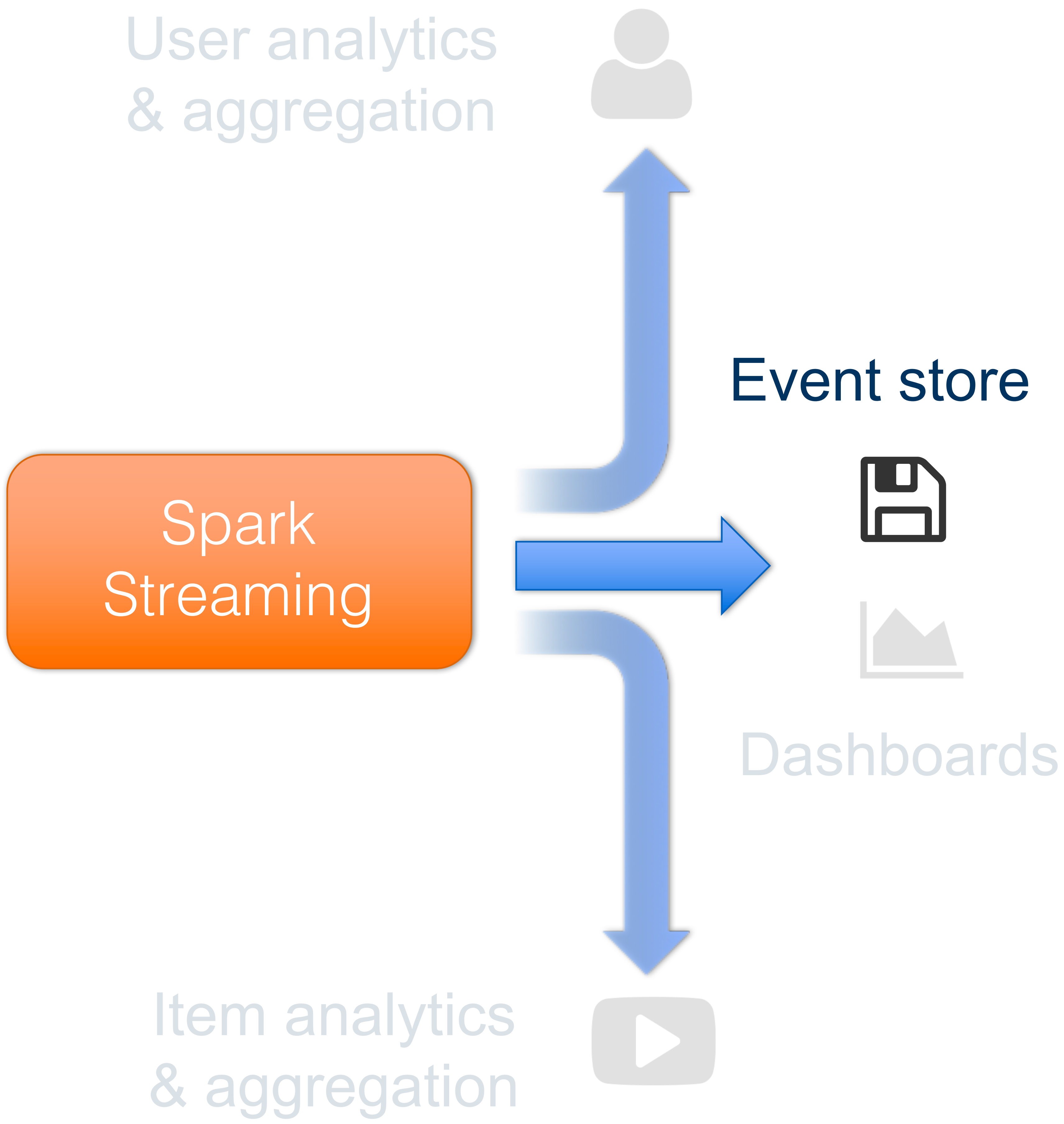
Event Data Pipeline

```
{
  "user_id": "1",
  "item_id": "10",
  "event_type": "page_view",
  "timestamp": 1476884080,
  "referrer": "http://spark.tc",
  "ip": "123.12.12.12",
  "device_type": "Smartphone",
  "user_agent_os": "Android",
  "user_agent_type": "Mobile Browser",
  "user_agent_family": "Chrome Mobile",
  "geo":"50.8503, 4.3517"
  ...
}
```

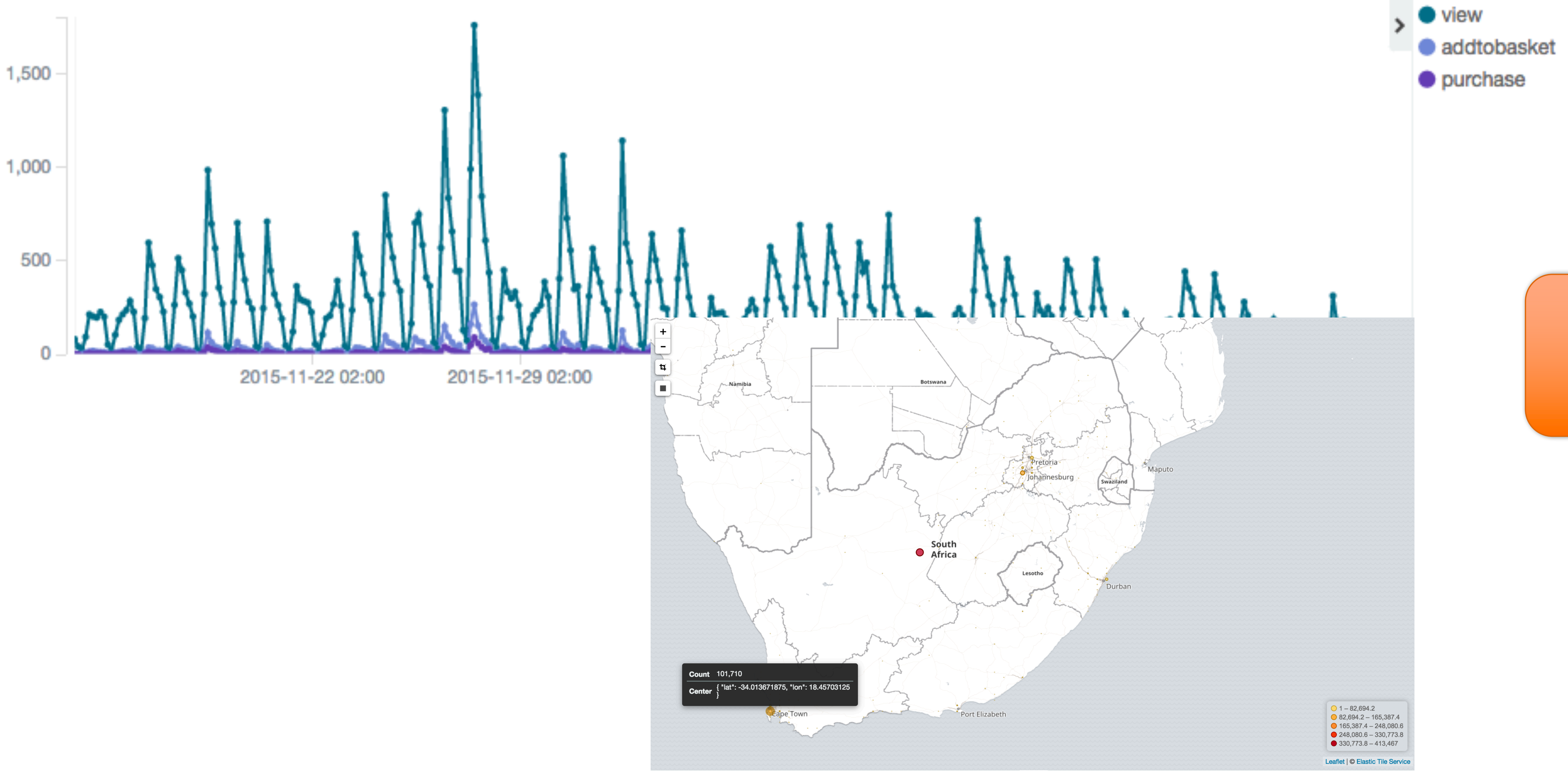


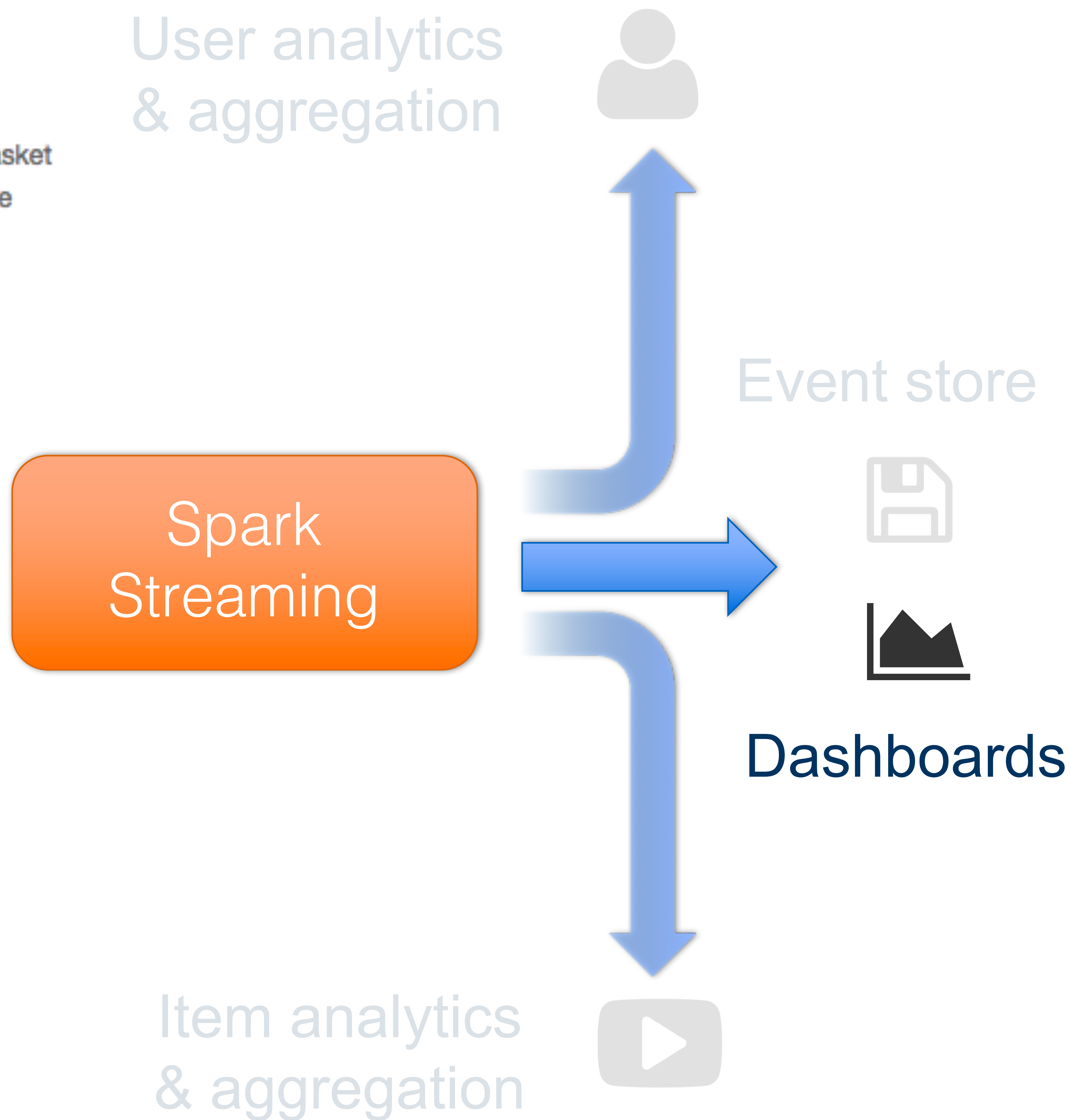
Write to Event Store

```
eventStream.foreachRDD { rdd =>
  rdd.map { case (key, event) =>
    val doc = Map(
      "userId"     -> event.userId,
      "itemId"     -> event.itemId,
      "eventType"  -> event.eventType,
      "timestamp"  -> event.timestamp,
      "weight"     -> event.weight,
      ...
    )
    val meta = Map(Metadata.ID -> event.eventId)
    (meta, doc)
  }.saveToEsWithMeta(Map("es.resource" -> "events-2016.11.14/events"))
}
```



Kibana Dashboards

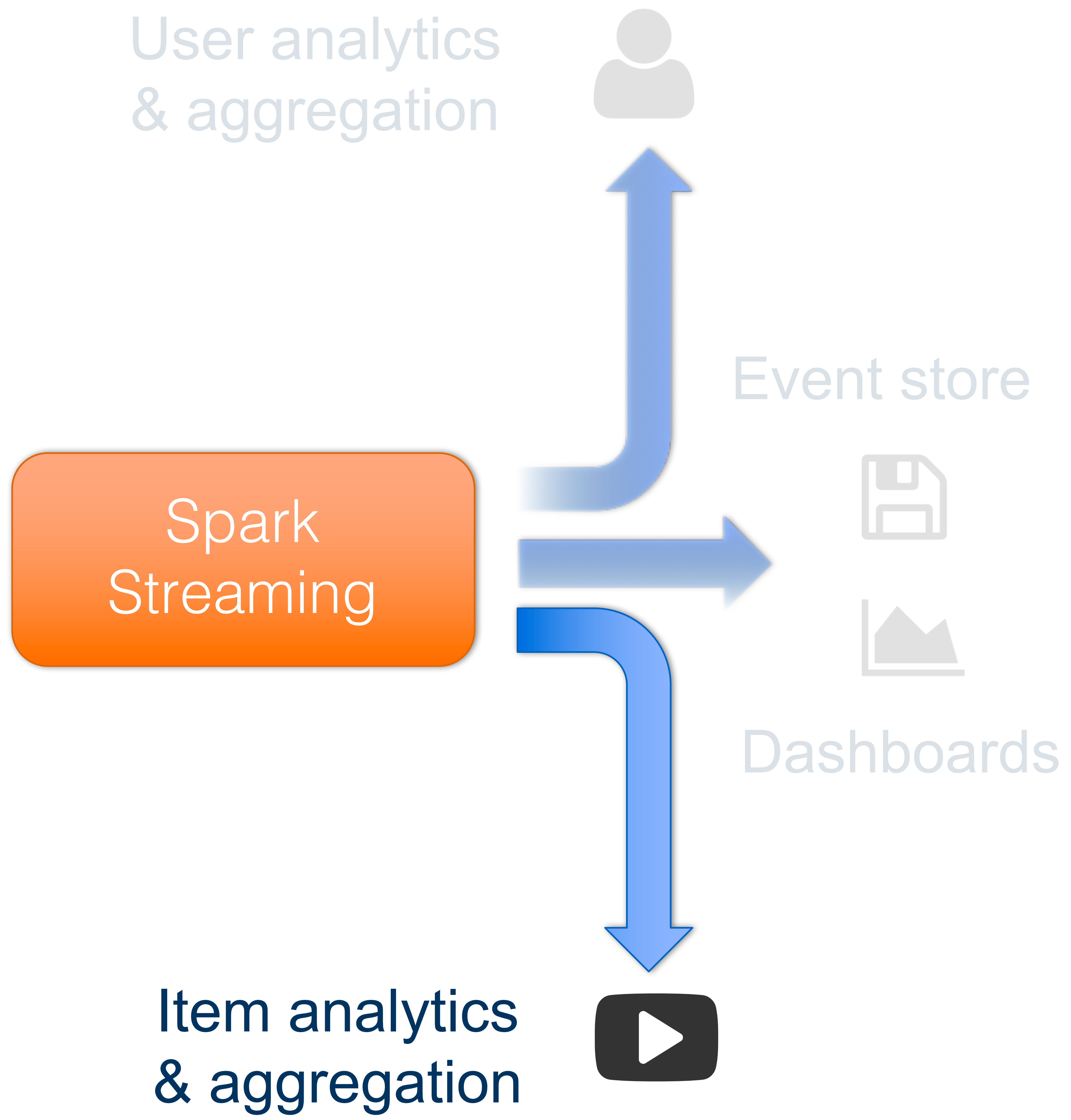




Item Metadata Analytics

```
{
  "item_id": "10",
  "name": "LOL Cats",
  "description": "catscatscats",
  "category": ["Cat Videos", "Humour", "Animals"],
  "tags": ["cat", "lol", "funny", "cats", "felines"],
  "created_date": 1476884080,
  "updated_date": 1476884080,
  "last_played_date": 1476946962,
  "likes": 100000,
  "author_id": "321",
  "author_name": "ilikecats",
  "channel_id": "CatVideoCentral",
  ...
}
```

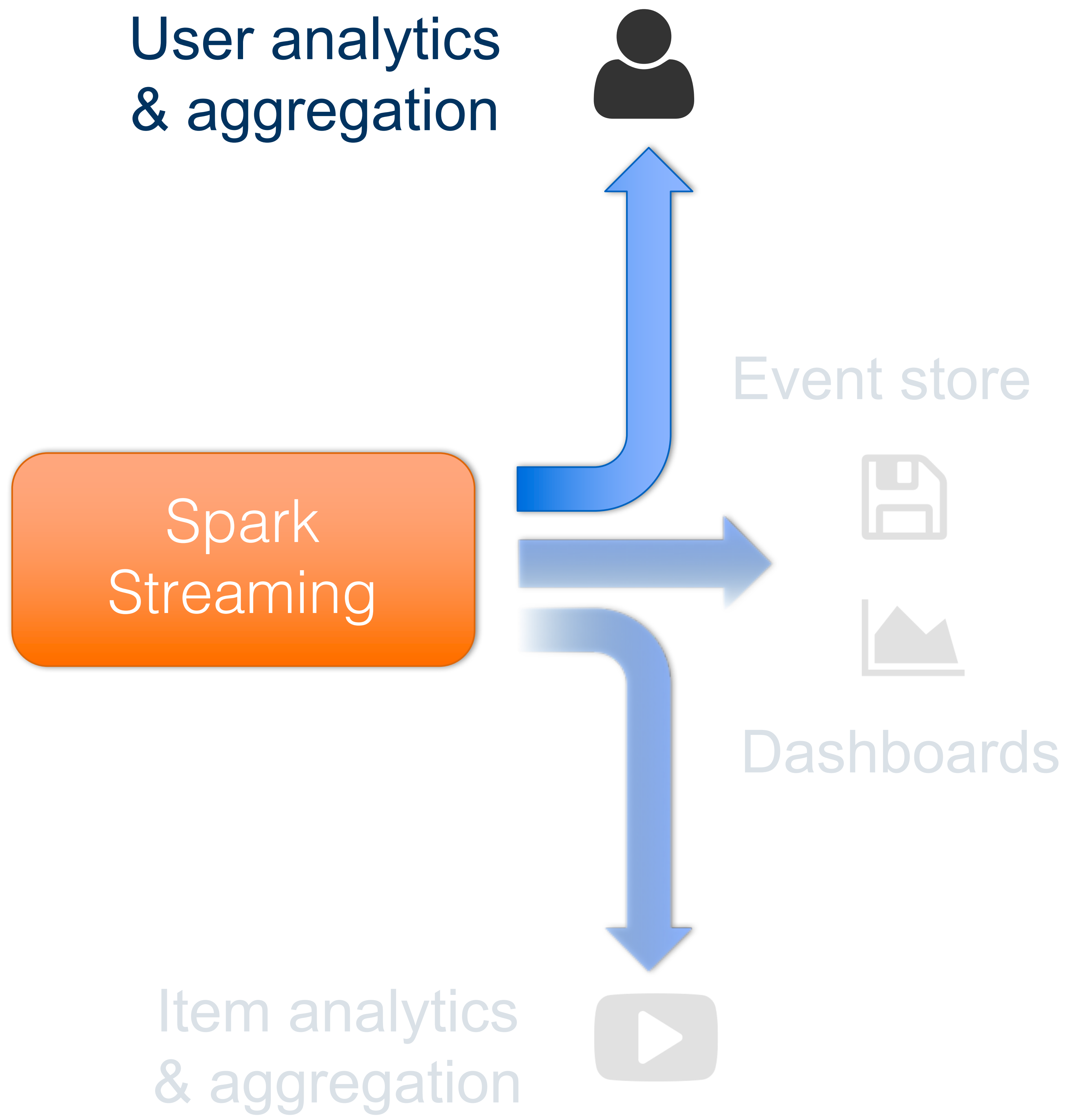
Aggregated activity metrics



User Metadata Analytics

```
{
  "user_id": "1",
  "name": "Joe Bloggs",
  "created_date": 1476884080,
  "updated_date": 1476946916,
  "last_active_date": 1476946962,
  "age": 32,
  "items": [{"id":"10","event_type":"purchase"},...]
  "country": "Spain",
  "city": "Seville",
  ...
}
```

Aggregated activity metrics &
item exclusions



Structured Streaming

```
val rawStream = spark
  .readStream
  .format("kafka")
  .option("kafka.bootstrap.servers",
          "host1:port1,host2:port2")
  .option("subscribe", "events")
  .load()
val eventStream = rawStream
  .selectExpr("CAST(value AS STRING)")
  .select(readEventUdf(...))
  .writeStream
  .foreach(new ESForeachWriter)
  .start()
```

Status

- Still early days
- Initial Kafka support in Spark 2.0.2
- No ES support yet – not clear if it will be a full-blown datasource or `ForeachWriter`
- For now, you can create a custom `ForeachWriter` for your needs

Spark ML for Collaborative Filtering

Collaborative Filtering

Matrix Factorization

$$\begin{bmatrix} 3 & & & \\ & 1 & & \\ & 5 & & 2 \\ 1 & & & \\ & & 2 & 1 \end{bmatrix} \Rightarrow \begin{bmatrix} -1.1 & 3.2 & 4.3 \\ 0.2 & 1.4 & 3.1 \\ 2.5 & 0.3 & 2.3 \\ 4.3 & -2.4 & 0.5 \\ 3.6 & 0.3 & 1.2 \end{bmatrix} \times \begin{bmatrix} 0.2 & 1.7 & 2.3 & 0.1 \\ 1.9 & 0.4 & 0.8 & -0.3 \\ 1.5 & -1.2 & 0.3 & 1.2 \end{bmatrix}$$

Collaborative Filtering

Prediction

$$
\begin{bmatrix} 3 & & & \\ & 1 & & \\ & 5 & & 2 \\ 1 & & & \\ & & 2 & 1 \end{bmatrix}
\Rightarrow
\begin{bmatrix} -1.1 & 3.2 & 4.3 \\ 0.2 & 1.4 & 3.1 \\ 2.5 & 0.3 & 2.3 \\ 4.3 & -2.4 & 0.5 \\ 3.6 & 0.3 & 1.2 \end{bmatrix}
\times
\begin{bmatrix} 0.2 & 1.7 & 2.3 & 0.1 \\ 1.9 & 0.4 & 0.8 & -0.3 \\ 1.5 & -1.2 & 0.3 & 1.2 \end{bmatrix}
$$

Collaborative Filtering

Loading Data in Spark ML


```
{
  "user_id": "1",
  "item_id": "10",
  "event_type": "page_view",
  "weight": 1.0,
  "timestamp": 1476884080,
  "referrer": "http://spark.tc",
  "ip": "123.12.12.12",
  "device_type": "Smartphone",
  "user_agent_os": "Android",
  "user_agent_type": "Mobile Browser",
  "user_agent_family": "Chrome Mobile",
  "geo":"50.8503, 4.3517"
  ...
}
```


```
df = spark
    .read
    .format("es")
    .load("demo/events")
```

```
+-------+-------+-----------+------+
|user_id|item_id| event_type|weight|
+-------+-------+-----------+------+
|      1|     10|  page_view|   1.0|
|      1|     15|  page_view|   1.0|
|      2|     23|  page_view|   1.0|
|      1|     10|   purchase|   5.0|
|      2|     23|add_to_cart|   2.0|
+-------+-------+-----------+------+
```

Alternating Least Squares

Implicit Preference Data

```
+-------+-------+-----------+------+
|user_id|item_id| event_type|weight|
+-------+-------+-----------+------+
|      1|     10|  page_view|   1.0|
|      1|     15|  page_view|   1.0|
|      2|     23|  page_view|   1.0|
|      1|     10|   purchase|   5.0|
|      2|     23|add_to_cart|   2.0|
+-------+-------+-----------+------+
```

```
+-------+-------+------+
|user_id|item_id|rating|
+-------+-------+------+
|      2|     23|   3.0|
|      1|     10|   6.0|
|      1|     15|   1.0|
+-------+-------+------+
```

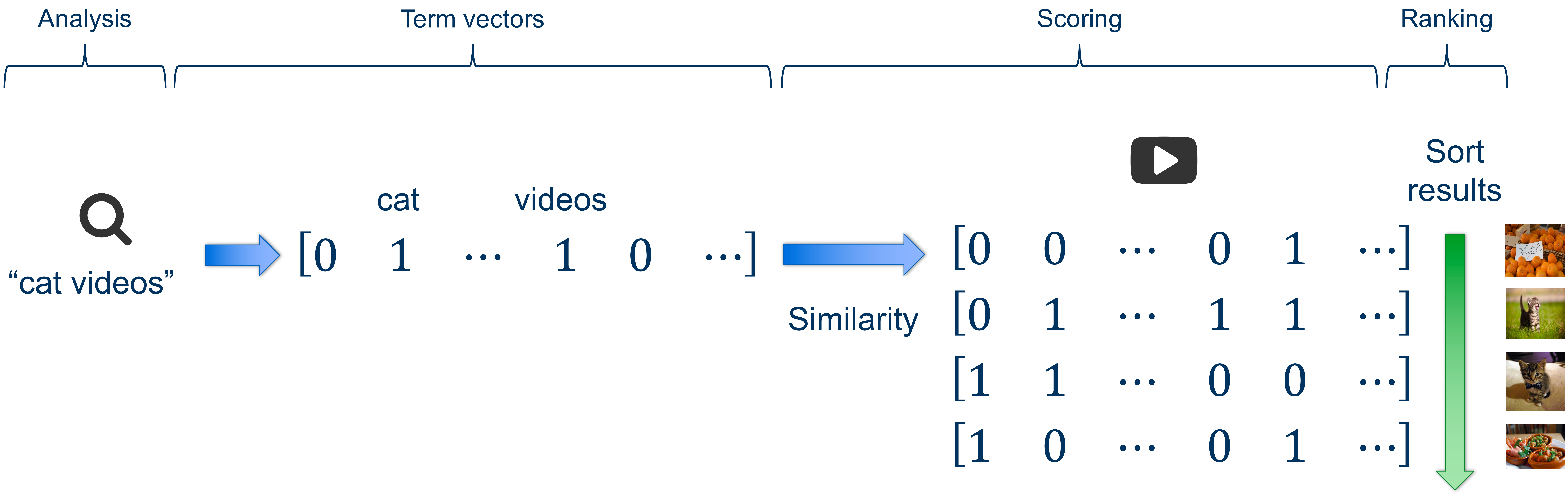
```
ratings = df
        .select("user_id", "item_id", "weight")
        .groupBy("user_id", "item_id")
        .sum().toDF("user_id", "item_id", "rating")
```

```
from pyspark.ml.recommendation import ALS
als = ALS(userCol="user_id",
          itemCol="item_id",
          ratingCol="rating",
          implicitPrefs=True)
model = als.fit(ratings)
```

Deploying & Scoring Recommendation Models

Prelude: Search

Full-text Search & Similarity



Recommendation

Can we use the same machinery?

Analysis ✗	Term vectors ✗	Scoring ?	Ranking ✓

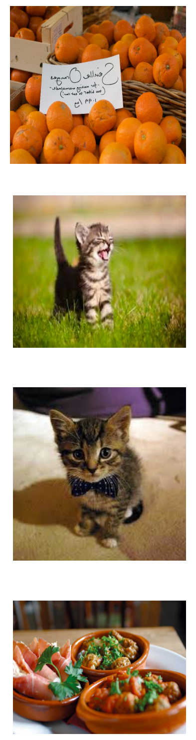
User (or item) vector

$$[1.2 \quad \cdots \quad -0.2 \quad 0.3]$$

Similarity

$$\begin{matrix} [0 & 0 & \cdots & 0 & 1 & \cdots] \\ [0 & 1 & \cdots & 1 & 1 & \cdots] \\ [1 & 1 & \cdots & 0 & 0 & \cdots] \\ [1 & 0 & \cdots & 0 & 1 & \cdots] \end{matrix}$$

Sort results



Dot product & cosine similarity
… the same as we need for recommendations!

Elasticsearch Term Vectors

Delimited Payload Filter

Raw vector

$$[1.2 \quad \cdots \quad -0.2 \quad 0.3]$$

Custom analyzer

0|1.2 ··· 3|-0.2 4|0.3

Term vector with payloads

```
'terms': {
  '0': {
    'term_freq': 1,
     'tokens': [
       {
         'payload': 'P5mZmg==',
         'position': 0
       }
     ]
  },
```

Elasticsearch Scoring

```
{
  "function_score": {
    "query" : {
      ...
    },
    "script_score": {
      "script": "payload_vector_score",
      "lang": "native",
      "params": {
        "field": "@model.factor",
        "vector": [1.2,...,-0.2,0.3],
        "cosine" : True
      }
    },
    "boost_mode": "replace"
  }
}
```

Custom scoring function

- Native script (Java), compiled for speed
- Scoring function computes dot product by:
  - For each document vector index (“term”), retrieve payload
  - `score += payload * query(i)`
- Normalizes with query vector norm and document vector norm for cosine similarity

Recommendation

Can we use the same machinery?

Analysis	Term vectors	Scoring	Ranking

User (or item) vector

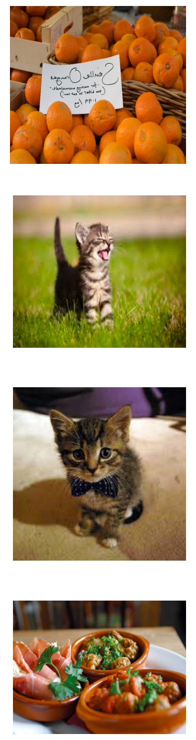
$$[1.2 \quad \cdots \quad -0.2 \quad 0.3]$$

Delimited payload filter

Custom scoring function

$$\begin{matrix} [-1.1 & 1.3 & \cdots & 0.4] \\ [1.2 & -0.2 & \cdots & 0.3] \\ [0.5 & 0.7 & \cdots & -1.3] \\ [0.9 & 1.4 & \cdots & -0.8] \end{matrix}$$

Sort results



Elasticsearch Scoring

We get search engine functionality for free!

```
{
  "function_score": {
    "query" : {
      ...
    },
    "script_score": {
      "script": "payload_vector_score",
      "lang": "native",
      "params": {
        "field": "@model.factor",
        "vector": [1.2,...,-0.2,0.3],
        "cosine" : True
      }
    },
    "boost_mode": "replace"
  }
}
```

```
{
  "item_id": "10",
  "name": "LOL Cats",
  "description": "catscatscats",
  "category": ["Cat Videos", "Humour", "Animals"],
  "tags": ["cat", "lol", "funny", "cats", "felines"],
  "created_date": 1476884080,
  "updated_date": 1476884080,
  "last_played_date": 1476946962,
  "likes": 100000,
  "author_id": "321",
  "author_name": "ilikecats",
  "channel_id": "CatVideoCentral",
  ...
}
```

Alternating Least Squares

Deploying to Elasticsearch

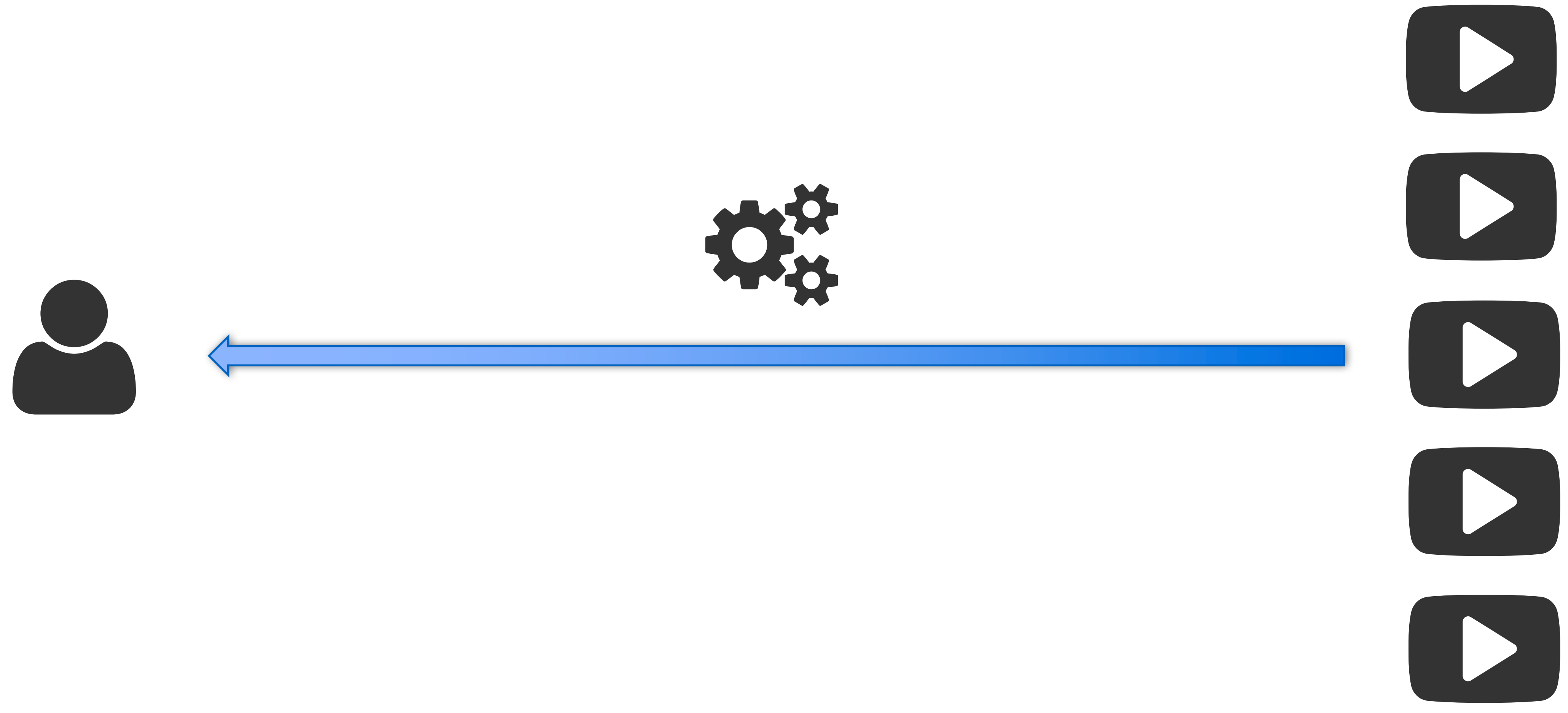
```
+---+--------------------+
| id|            features|
+---+--------------------+
| 10|[-0.31136435, 0.4...|
| 20|[0.35291243, 0.13...|
| 30|[-0.19601235, 0.6...|
| 40|[-0.23222291, 0.8...|
| 50|[-0.14678353, 0.4...|
+---+--------------------+
```

```
movie_vectors.write.format("es")
    .option("es.mapping.id", "id")
    .option("es.write.operation", "update")
    .save("demo/movies", mode="append")
```

Monitoring & Feedback

System Events

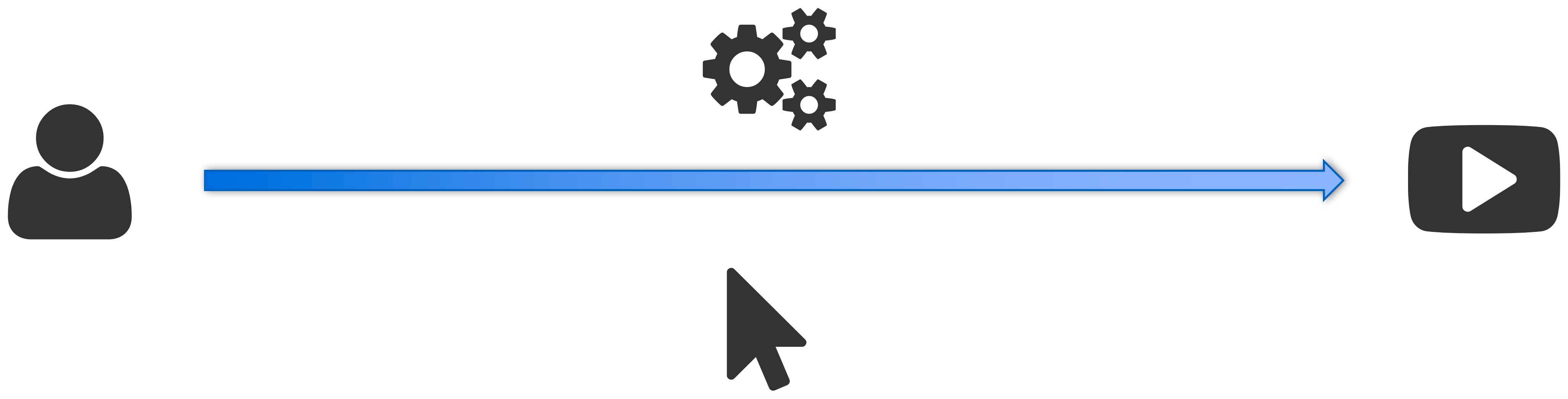
Logging Recommendations Served



```
{
  "event_id": "rec123",
  "user_id": "1",
  "item_ids": ["10", "20", "34", "13", "43"],
  "event_type": "recommendation",
  "model_id": "model456",
  "timestamp": 1476884080,
  ...
}
```

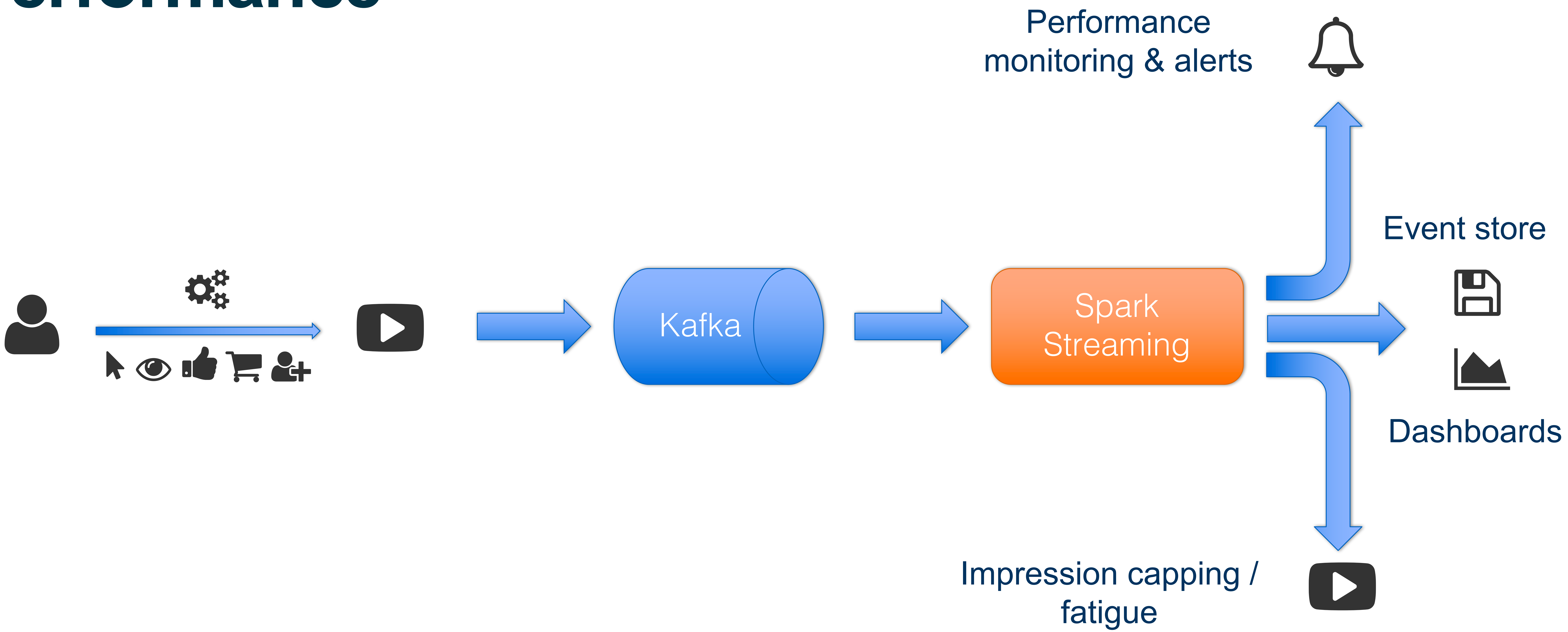
System Events

Logging Recommendation Actions



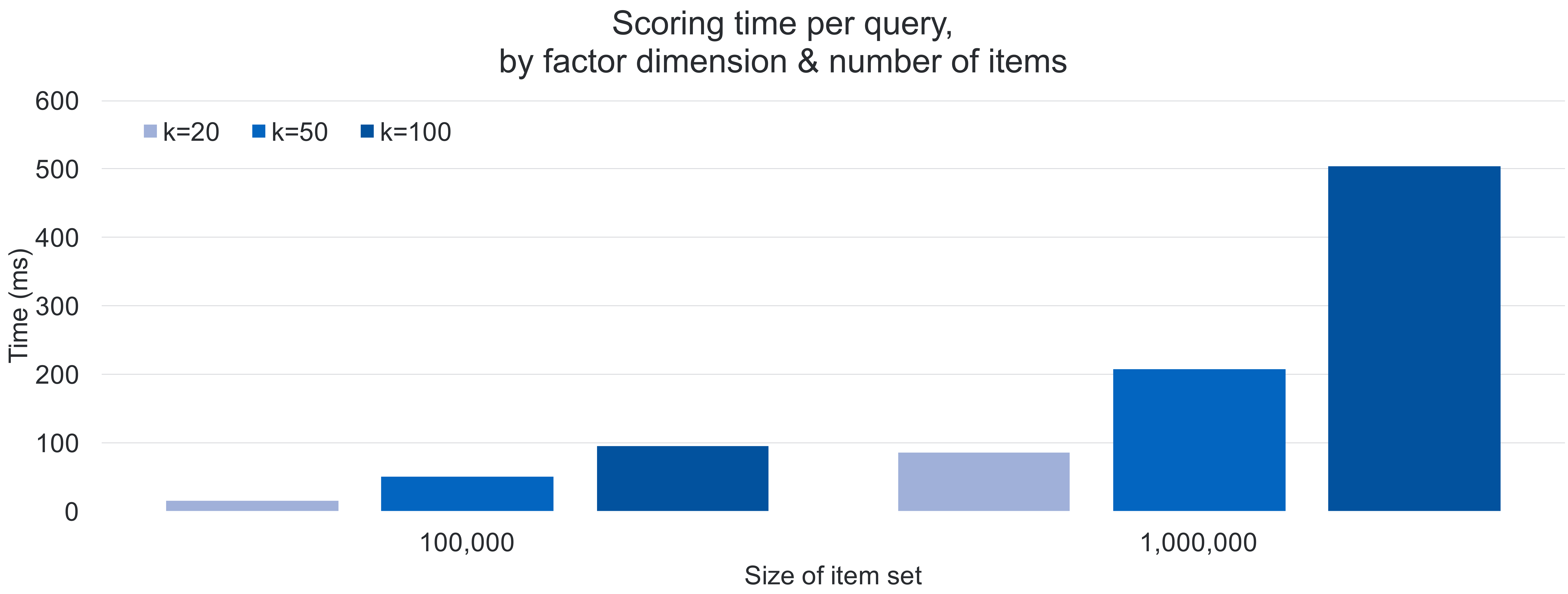

```
{
  "event_id": "rec123",
  "user_id": "1",
  "item_ids": ["10", "20", "34", "13", "43"],
  "actions": [
    {"item_id":"20","action":"click","timestamp":...},
    ...
  ],
  "event_type": "recommendation",
  "model_id": "model456",
  "timestamp": 1476884080,
  ...
}
```

Tracking Performance



Scaling Model Scoring

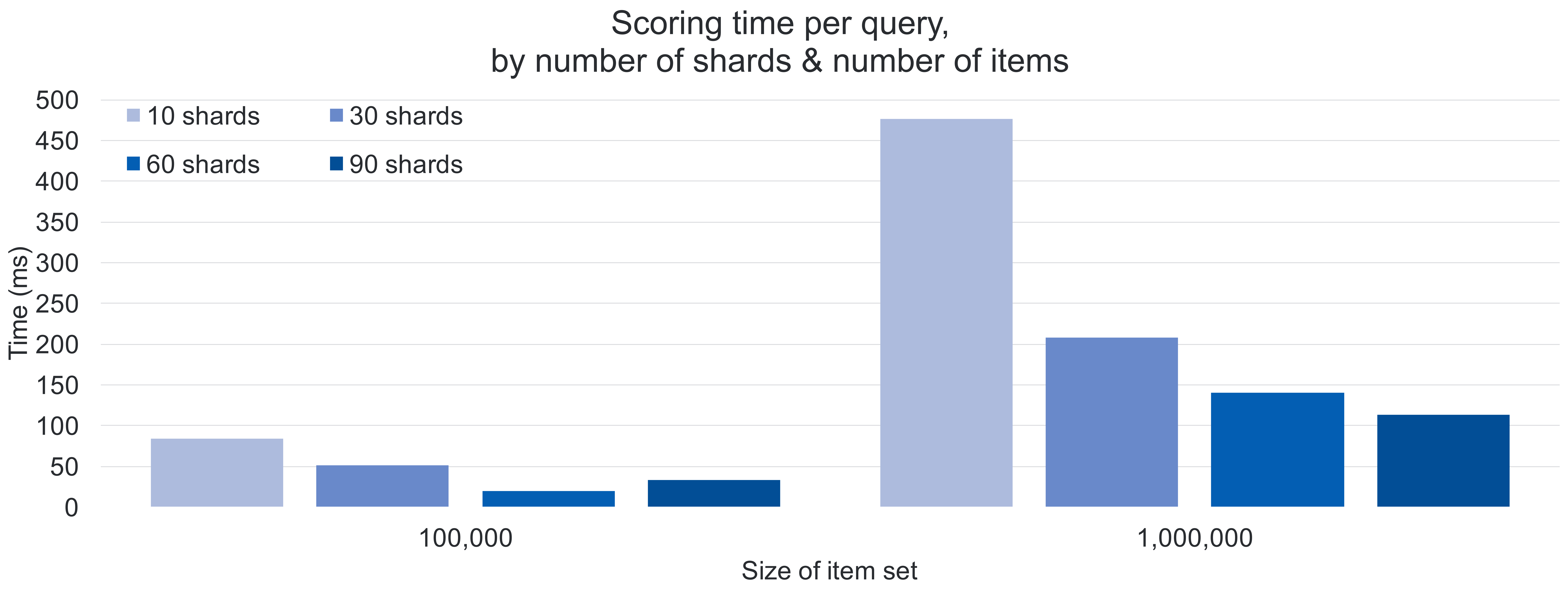
Scoring Performance



**3x nodes, 30x shards*

Scoring Performance

Increasing number of shards



3x nodes, k=50

Scoring Performance

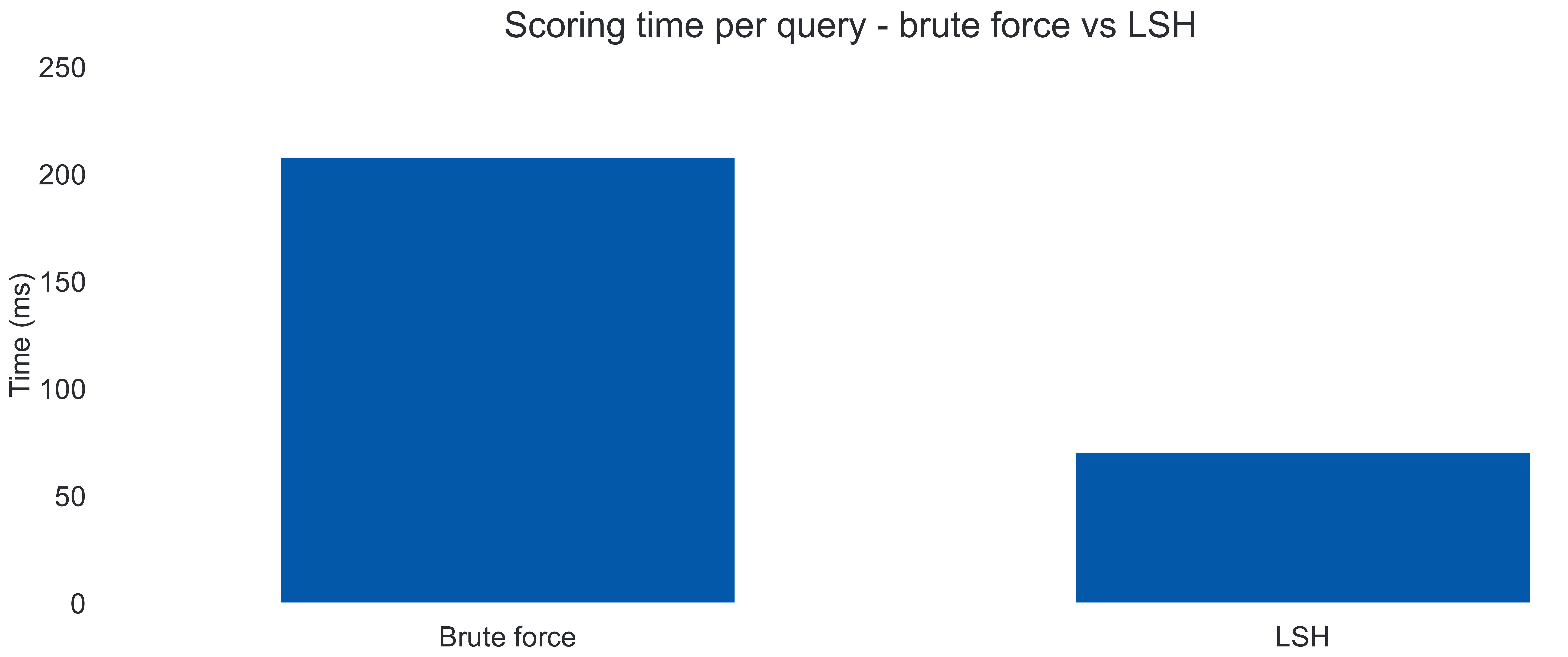
```
{
  "item_id": "10",
  "name": "LOL Cats",
  "@model" : {
    "buckets" : [
      "4_00001000",
      ...,
      "0_11010011" ],
    "factor" : "0|-1.3 1|0.05 ... "
    ...
  }
  ...
}
```

Locality Sensitive Hashing

- LSH hashes each input vector into *L* “hash tables”. Each table contains a “hash signature” created by applying *k* hash functions.
- Standard for cosine similarity is *Sign Random Projections*
- At indexing time, create a “bucket” by combining hash table id and hash signature
- Store buckets as part of item model metadata
- At scoring time, filter candidate set using term filter on buckets of query item
- Tune LSH parameters to trade off speed / accuracy
- LSH coming soon to Spark ML – [SPARK-5992]

Scoring Performance

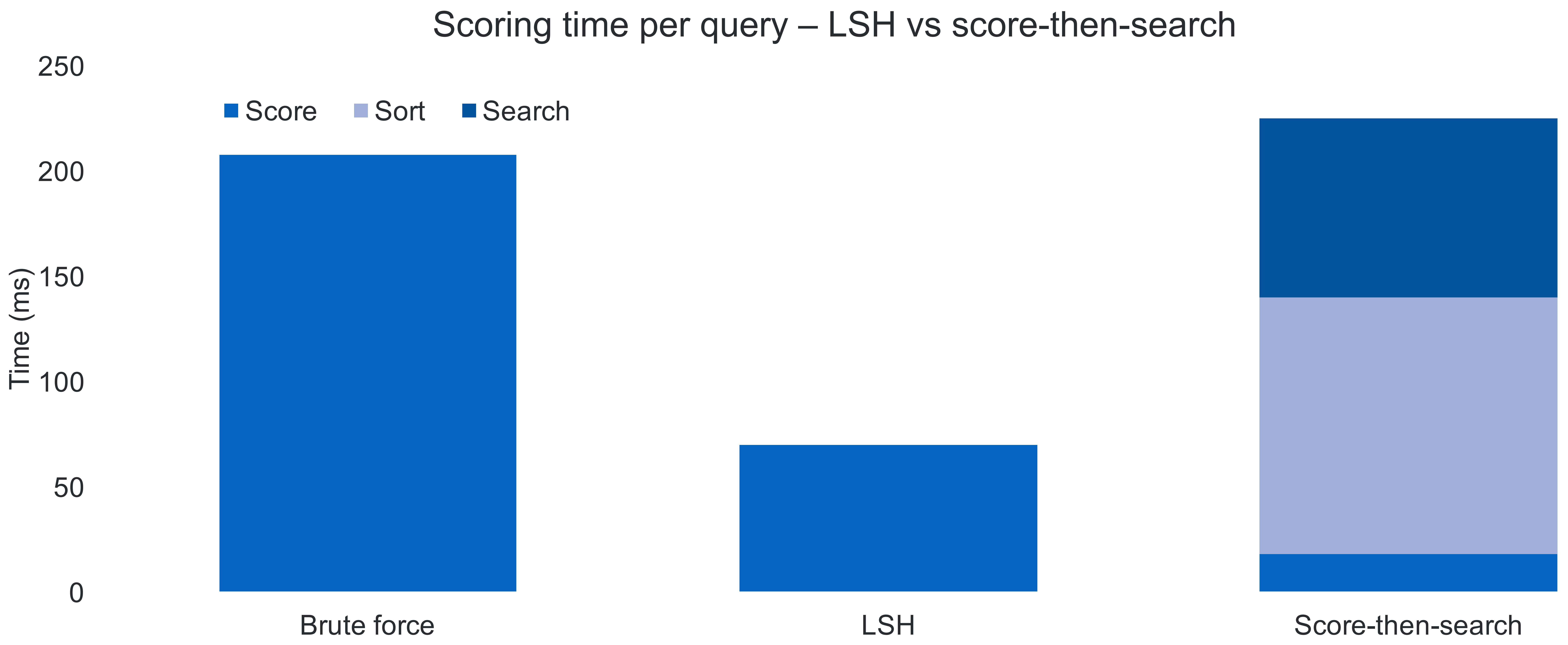
Locality Sensitive Hashing



**3x nodes, 30x shards, k=50, 1,000,000 items*

Scoring Performance

Comparison to “score then search”



**3x nodes, 30x shards, k=50, 1,000,000 items*

Demo

Future Work

Future Work

- Apache Solr version of scoring plugin (any takers?)
- Investigate ways to improve Elasticsearch scoring performance
  - Performance for LSH-filtered scoring should be better!
  - Can we dig deep into ES scoring internals to combine efficiency of matrix-vector math with ES search & filter capabilities?
- Investigate more complex models
  - Factorization machines & other contextual recommender models
  - Scoring performance
- Spark Structured Streaming with Kafka, Elasticsearch & Kibana
  - Continuous recommender application including data, model training, analytics & monitoring

References

- Elasticsearch
- Elasticsearch Spark Integration
- Spark ML ALS for Collaborative Filtering
- Collaborative Filtering for Implicit Feedback Datasets
- Factorization Machines
- Elasticsearch Term Vectors & Payloads
- Delimited Payload Filter
- Vector Scoring Plugin
- Kafka & Spark Streaming
- Kibana

Thanks!

https://github.com/MLnick/elasticsearch-vector-scoring