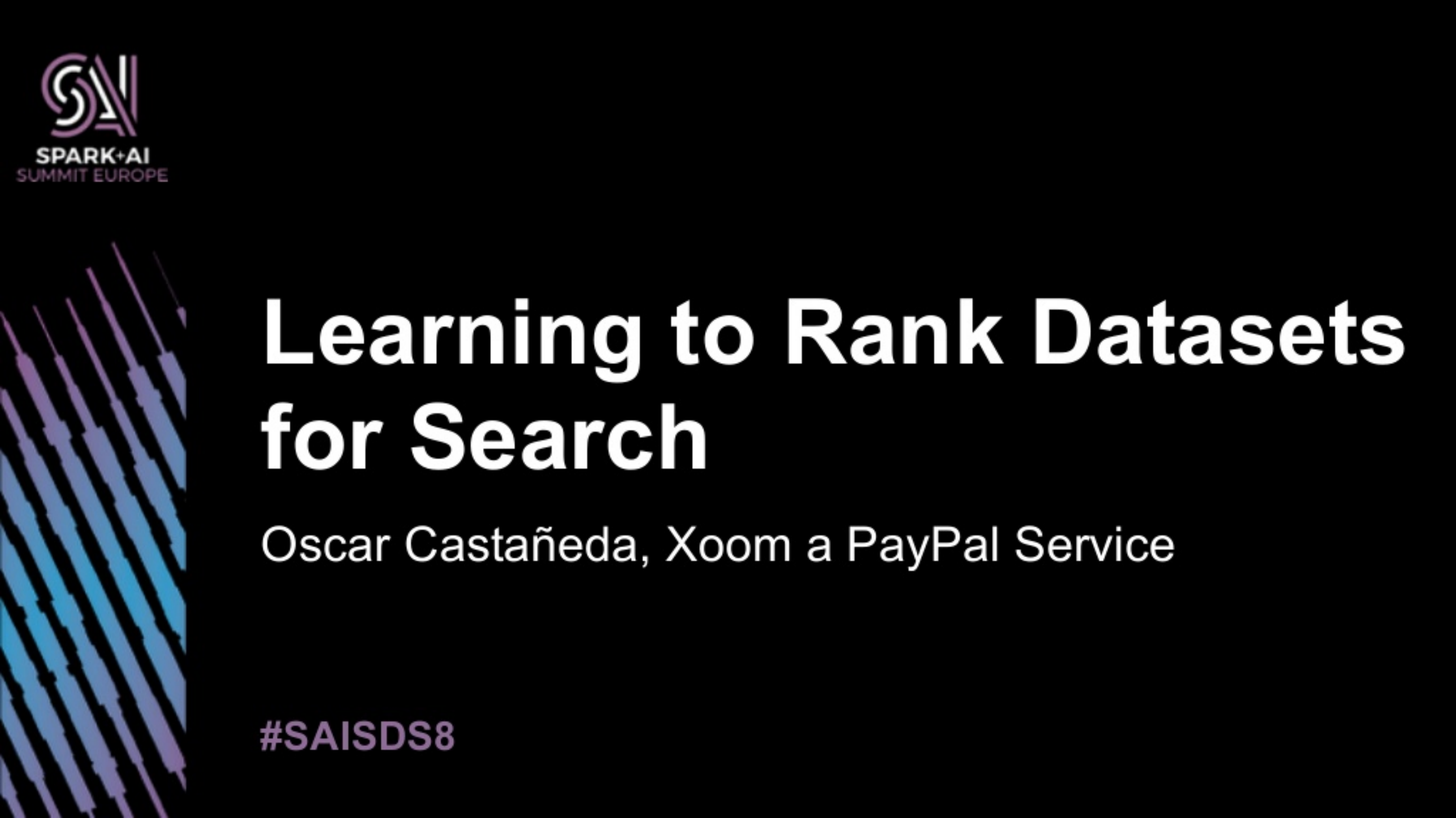


Learning to Rank Datasets for Search

Oscar Castañeda, Xoom a PayPal Service

#SAISDS8

About

- Data Scientist at Xoom a PayPal service.

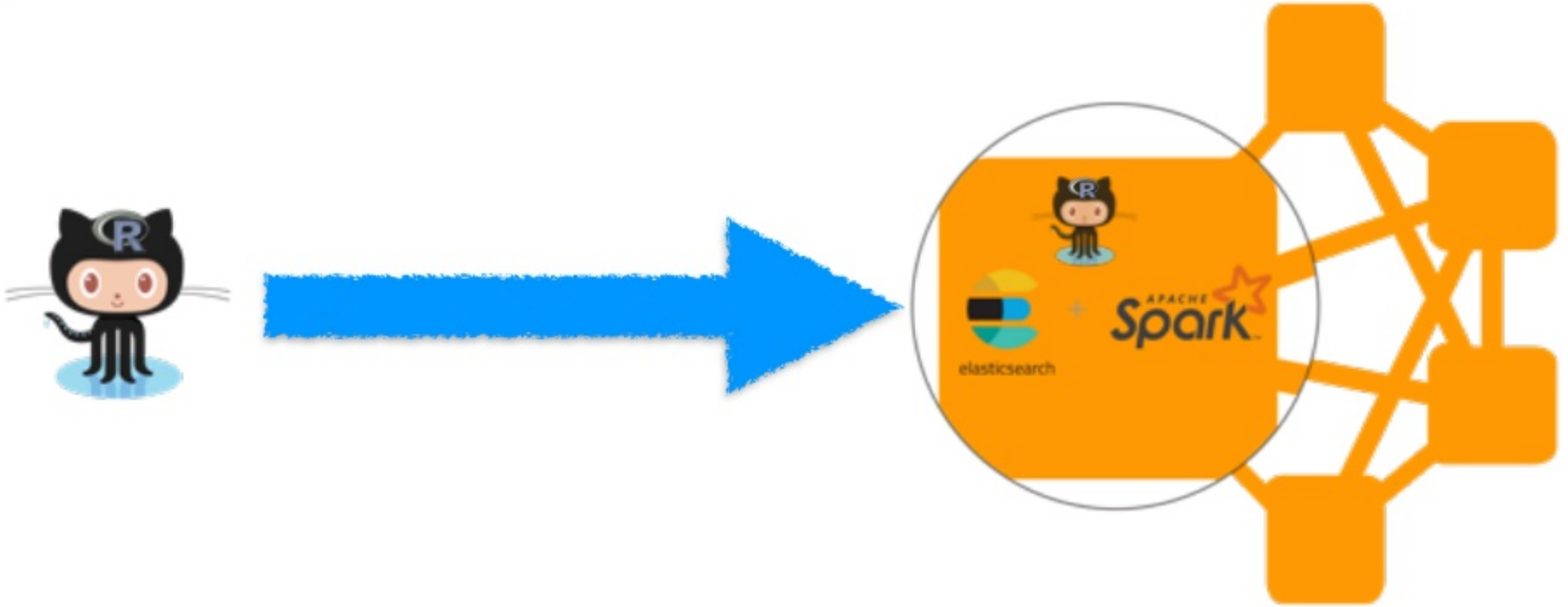
- Interests:
  - Data Management,
  - Dataset Search,
  - Learning to Rank.

Spark cluster with Elasticsearch

Elasticsearch

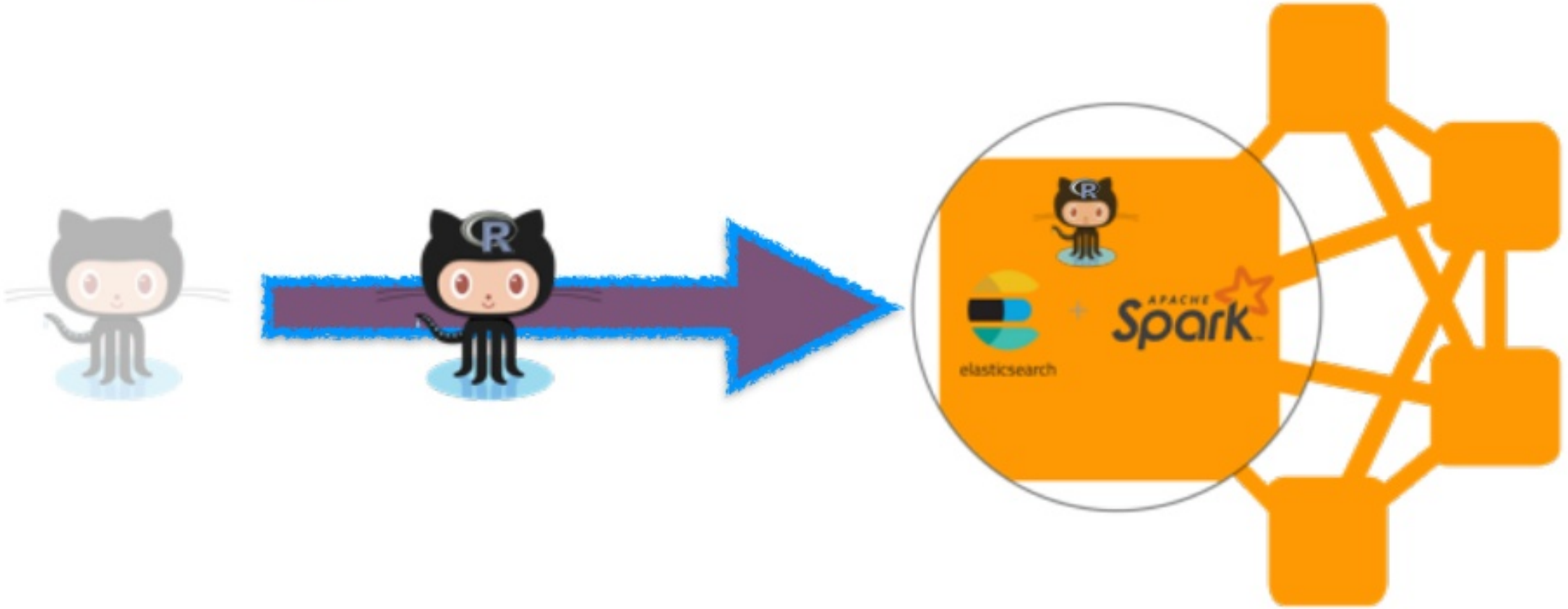
http://bit.ly/2cbM9BO

Spark cluster with Elasticsearch Inside

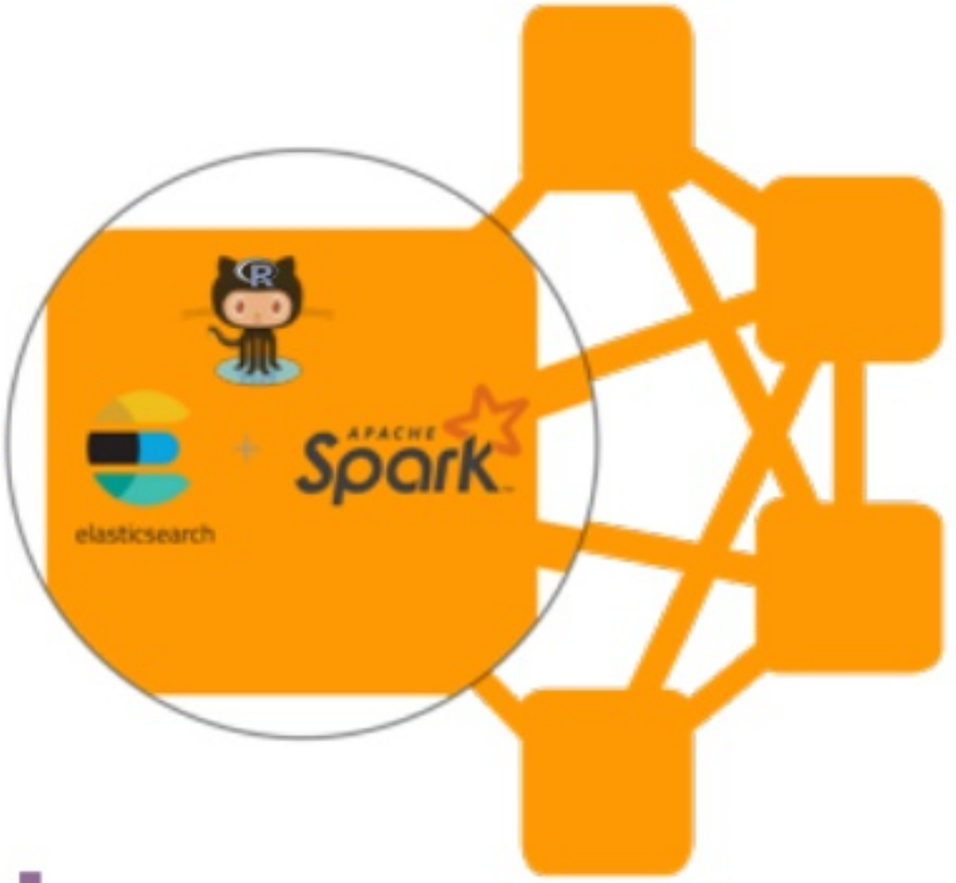


And Indexed RDatasets

Learning to Rank Datasets



Learning to Rank Datasets



for Search!

Agenda

- Problem Statement and Motivation
- Elasticsearch Learning to Rank
- Data Pipeline: metadata extraction, judgement list extraction
- Demo: Beginnings of a Dataset Search Engine with Machine-learned relevance ranking.
- Q&A

Problem Statement (1)

- Despite datasets being a key corporate asset they are generally not given the importance they deserve and as a result they are hard to find.

Problem Statement (2)

- Specifically, teams within organizations have a hard time finding datasets relevant to their function.

Topics

- Indexing

Topics

- Indexing (Spark Summit East 2017).

Topics

- Indexing (Spark Summit East 2017).
- Ranking

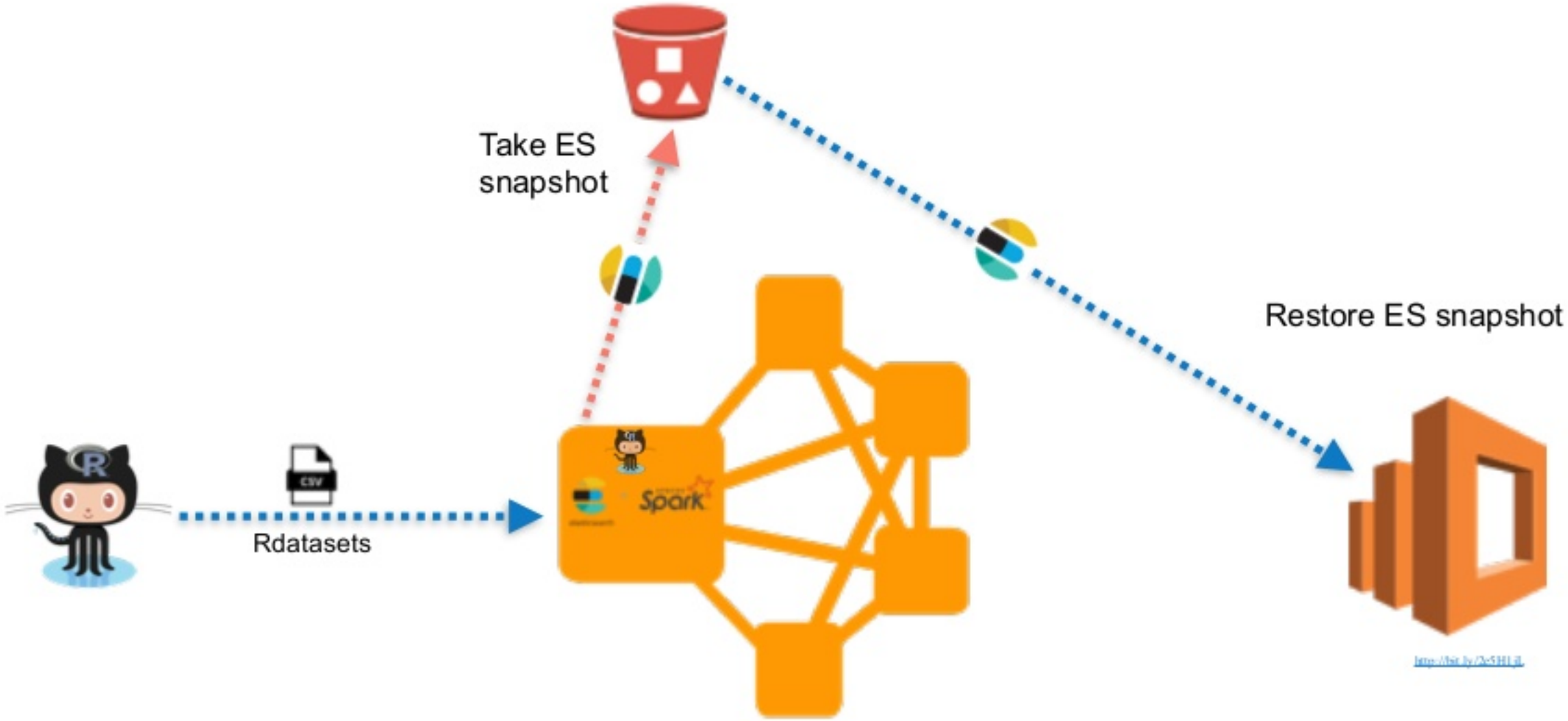
Topics

- Indexing (Spark Summit East 2017).
- Ranking => today's topic!

Questions

- How are datasets ranked?
- Can judgement lists (useful for ranking) be generated at dataset production time?

Overview

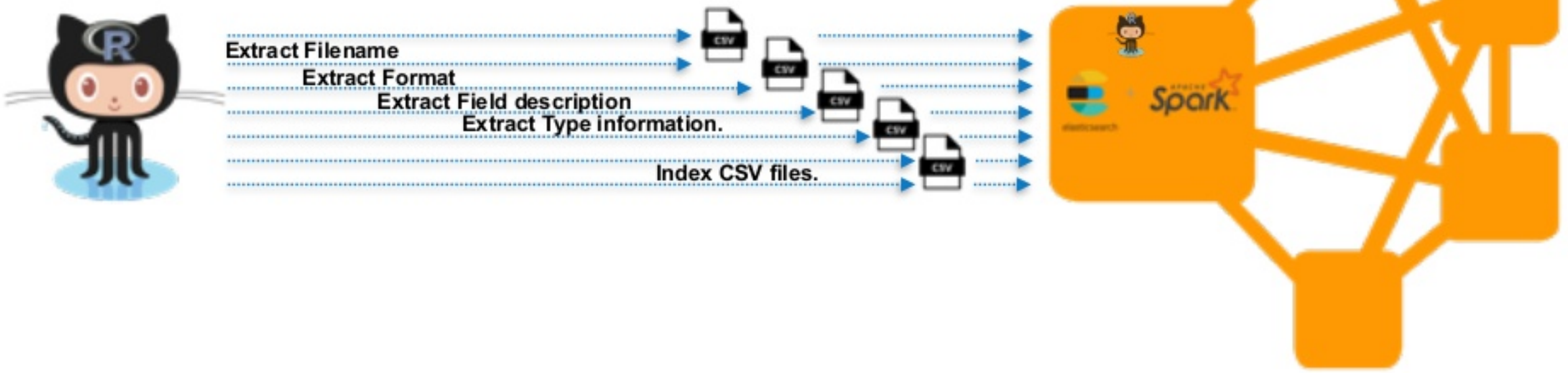


Overview

Data Pipelines:

- Extract Filename, Format, Field description.
- Extract Type information.
- Index CSV files.

Rdatasets



Overview

Data Lake

Overview

Data Lake

Motivation (1)

- *Organizing, indexing and ranking* Datasets:

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- *Organizing, indexing and ranking* Datasets:
  - Produced by individual data pipelines
  - On Data Lake(s)

Motivation (2)

- Produce a *ranking function for datasets* that are generated as part of running data pipelines.

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- Produce a *ranking function for datasets* that are generated as part of running data pipelines.
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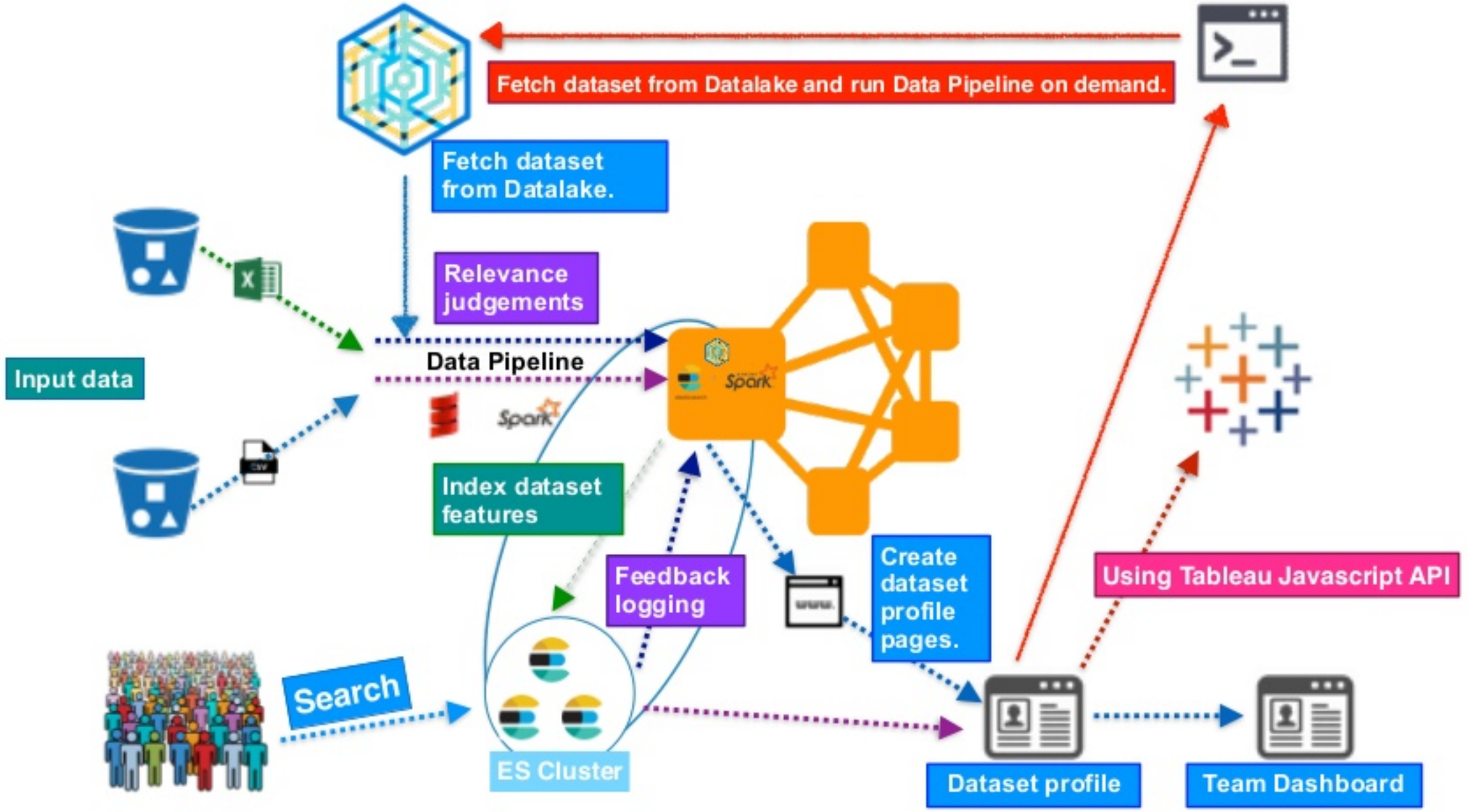
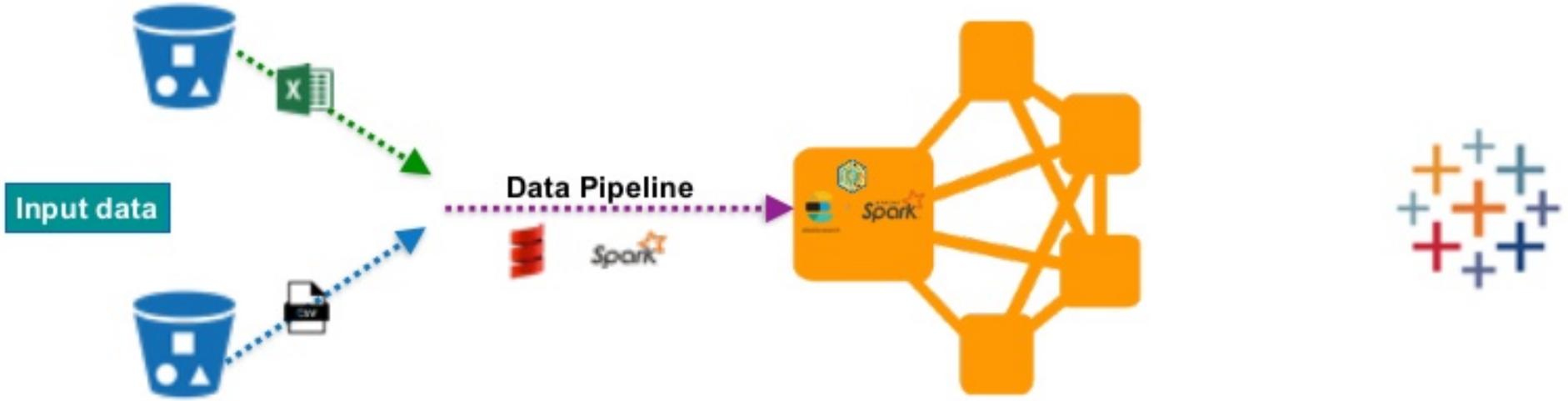
  - In a feedback loop leveraging click-through data on dataset profile pages.

Organizing, Indexing and Ranking Datasets



Organizing, Indexing and Ranking Datasets



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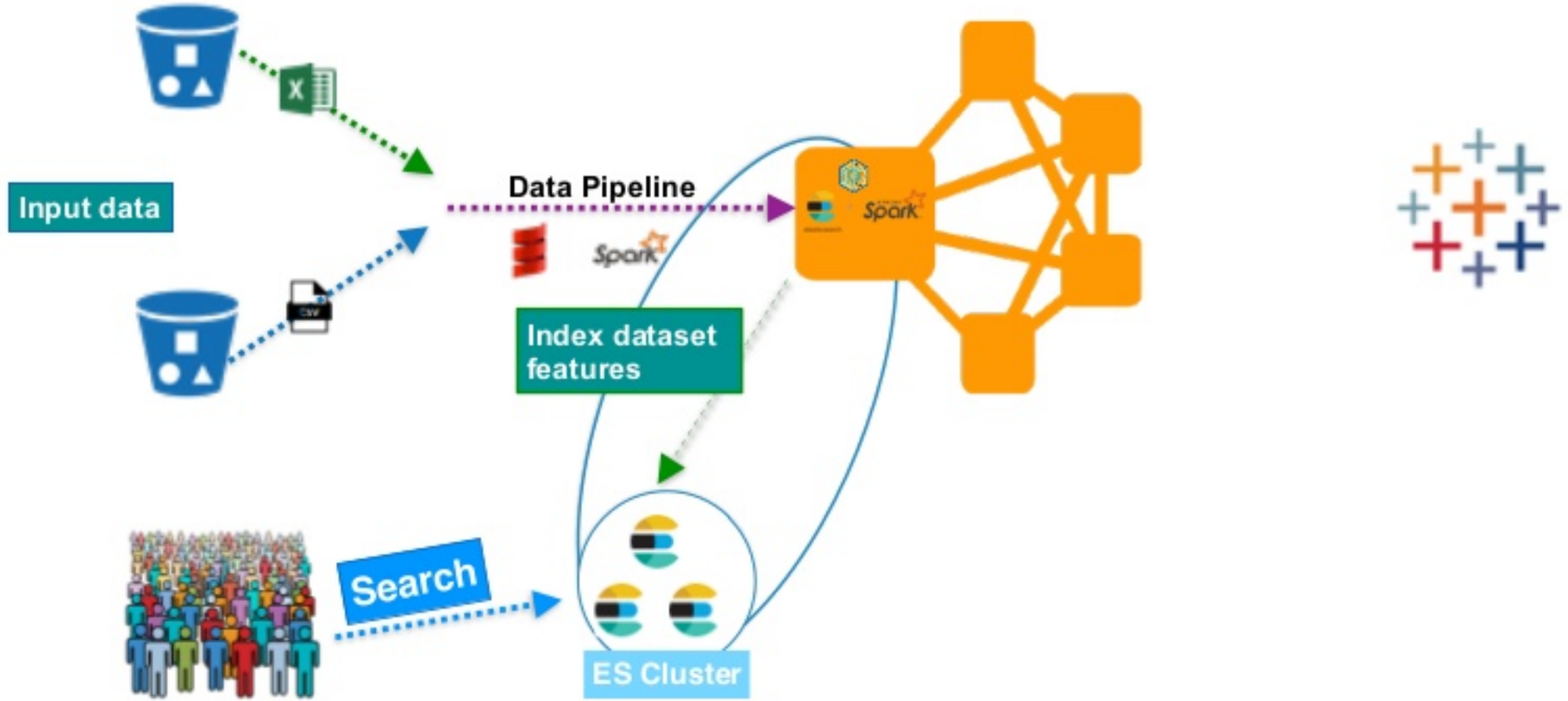
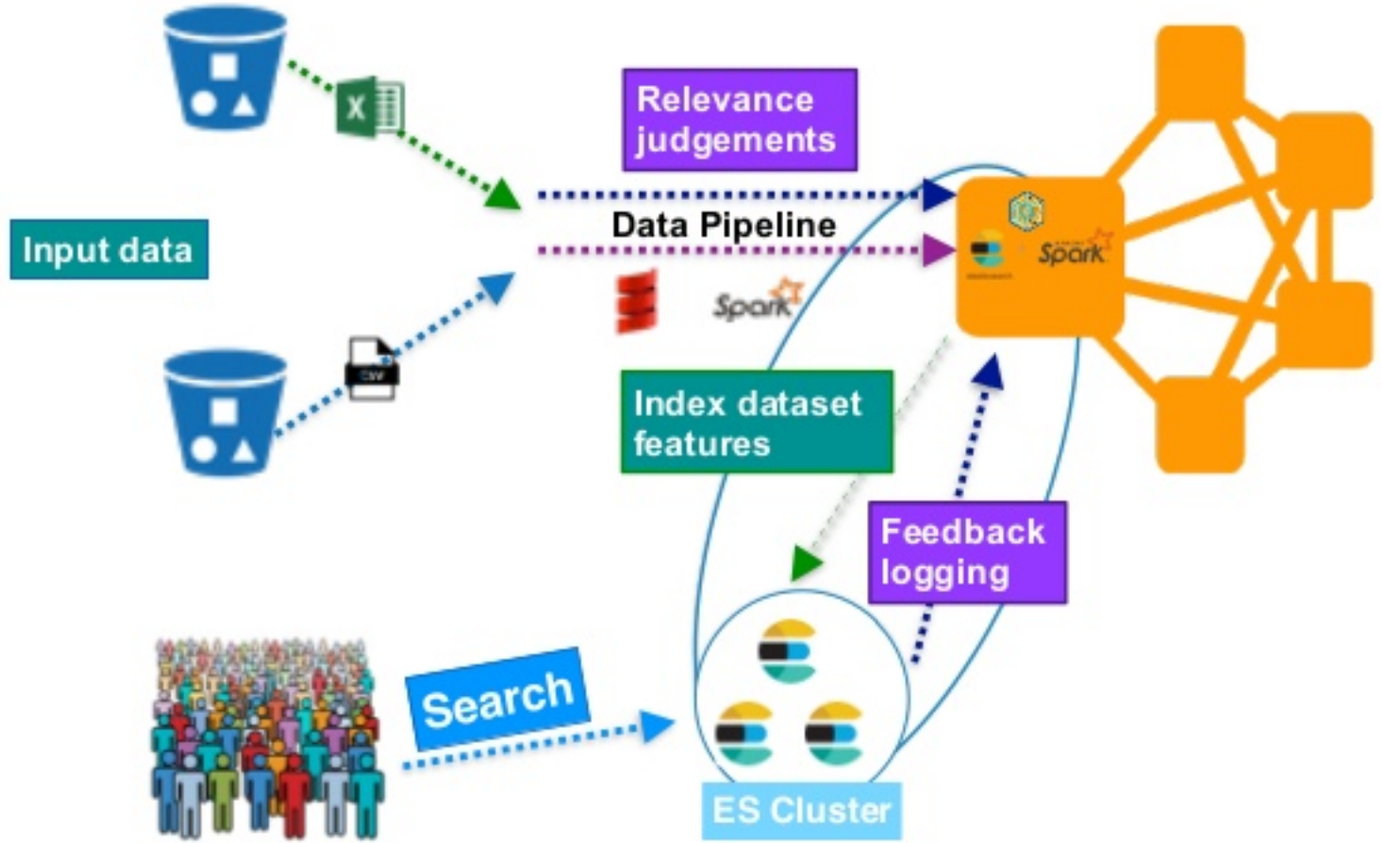


Organizing, Indexing and Ranking Datasets



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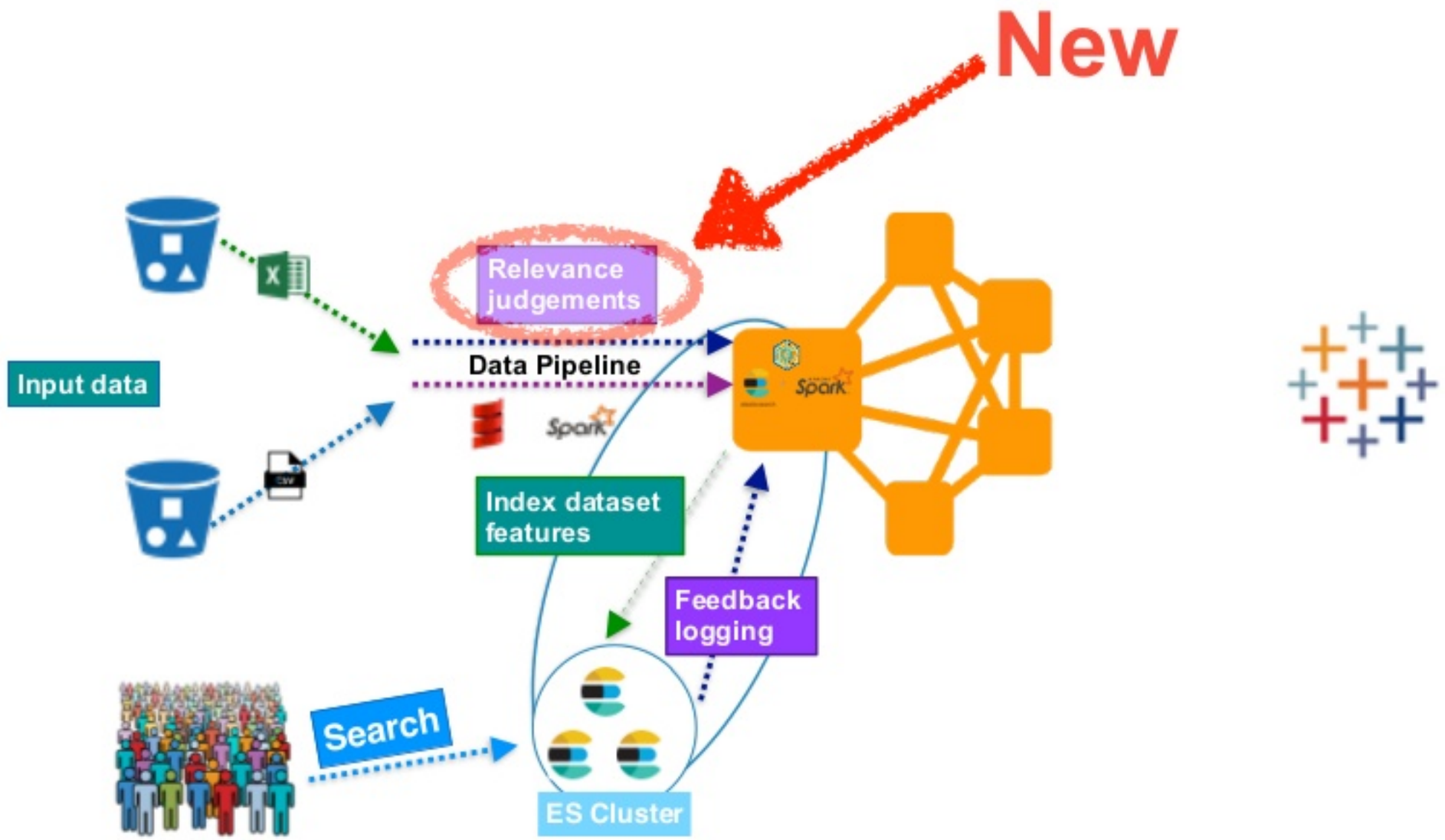

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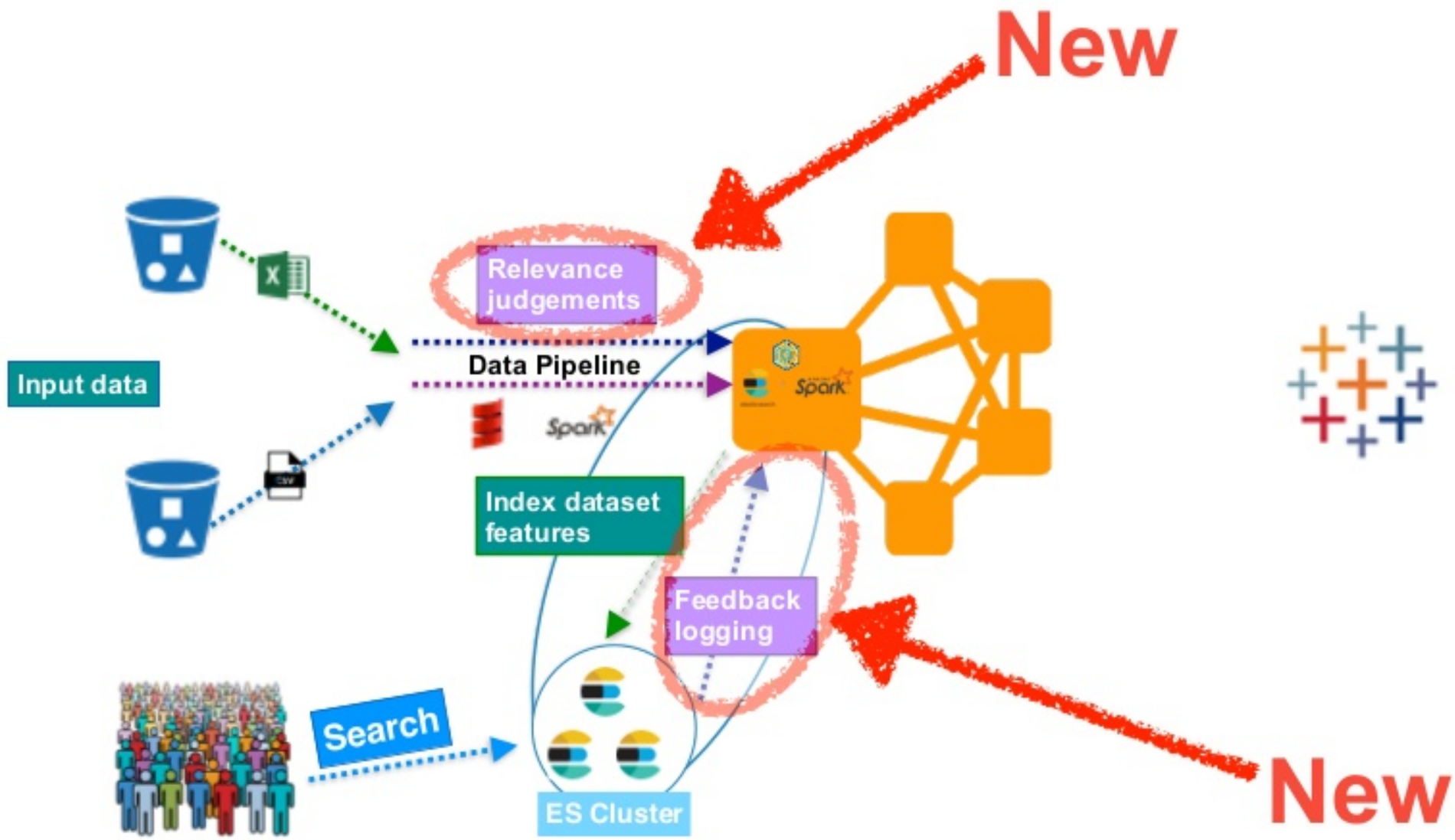

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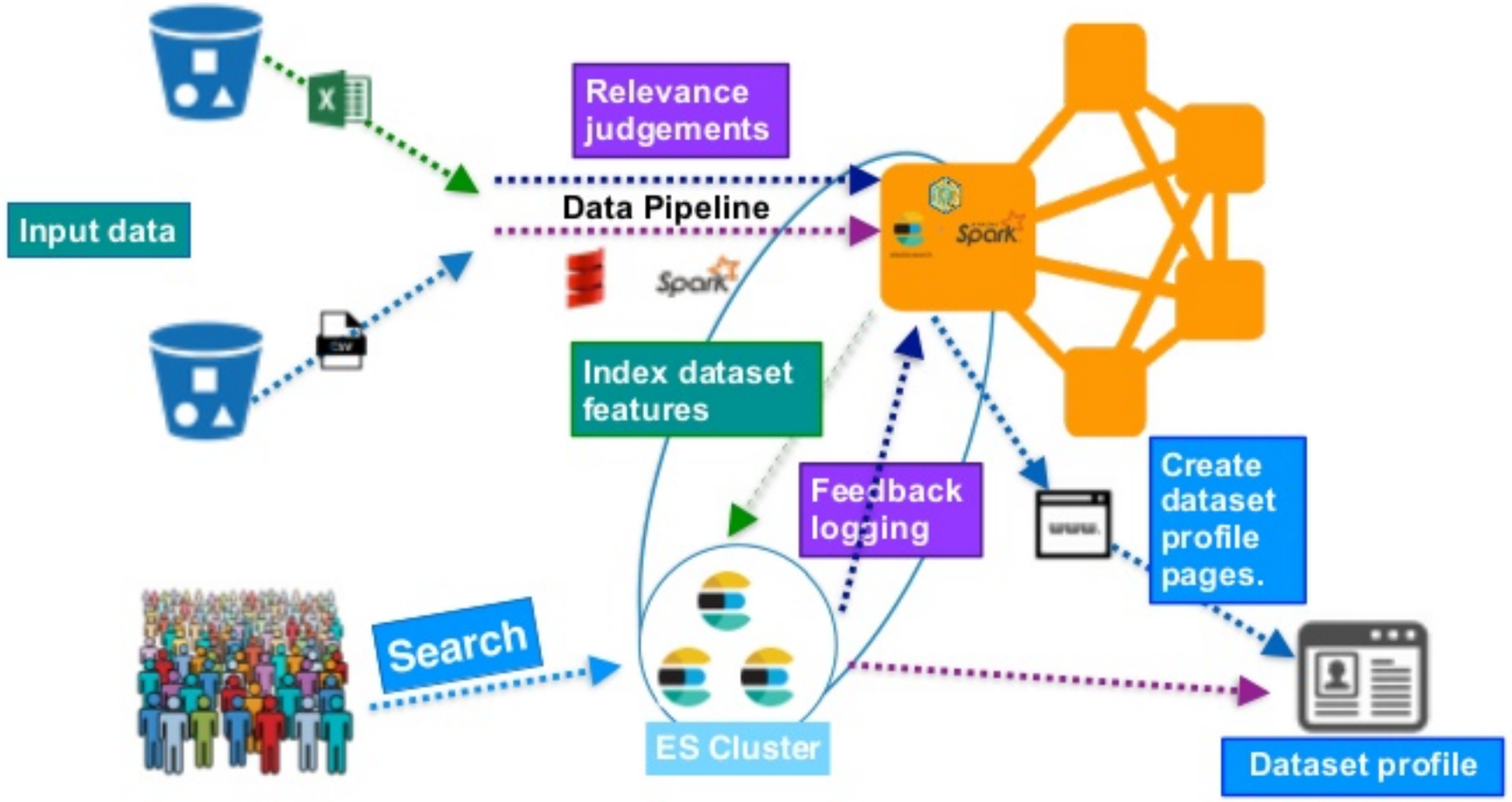

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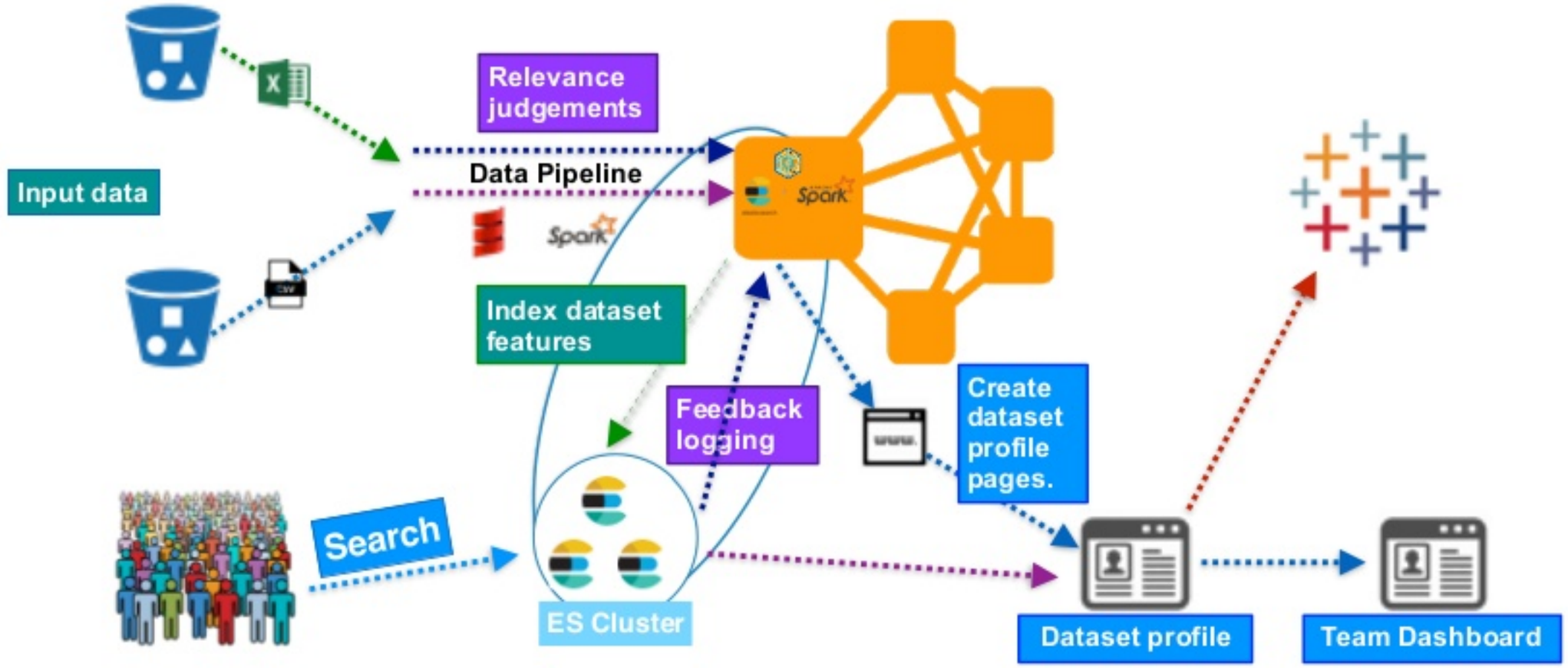

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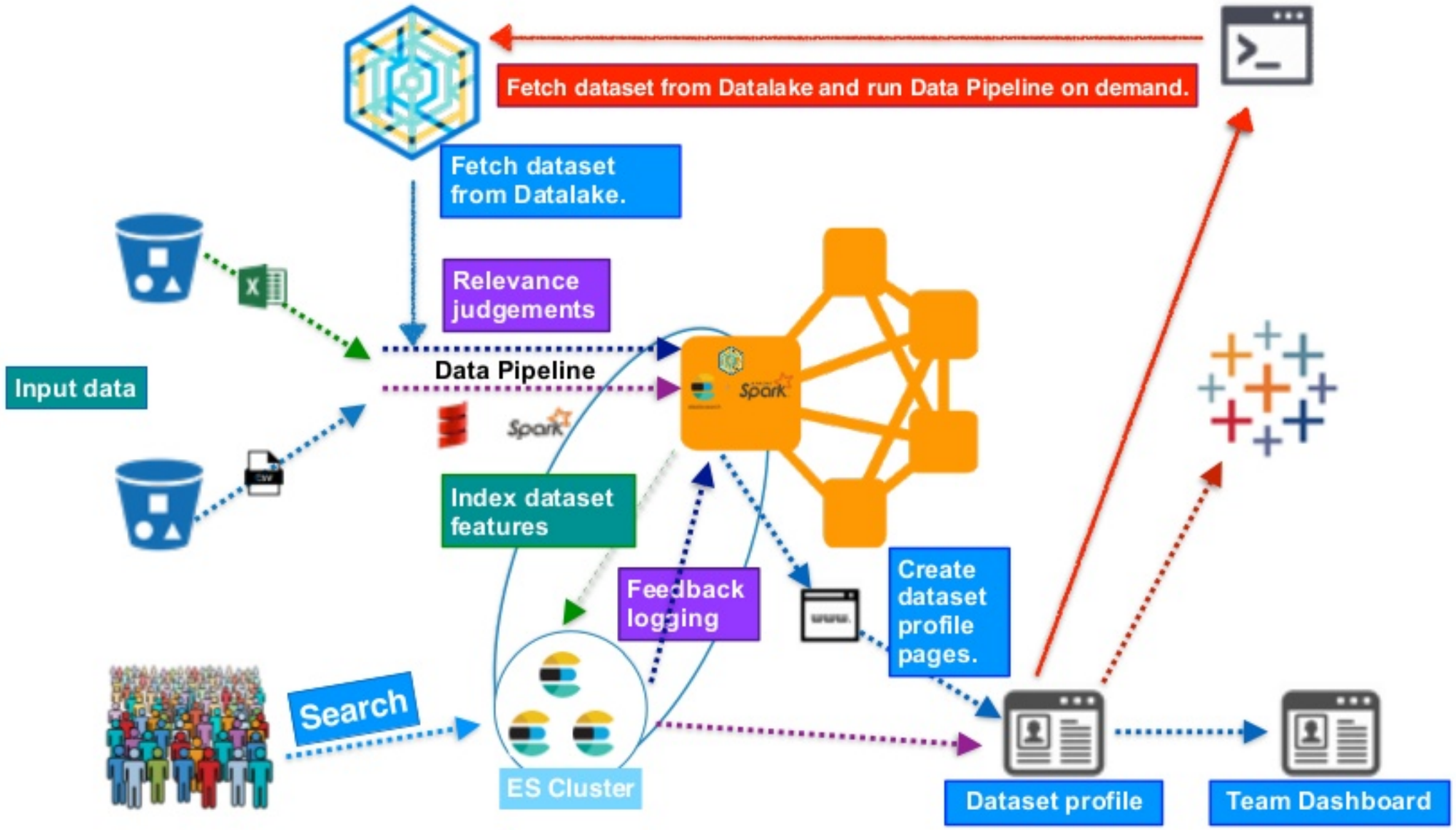
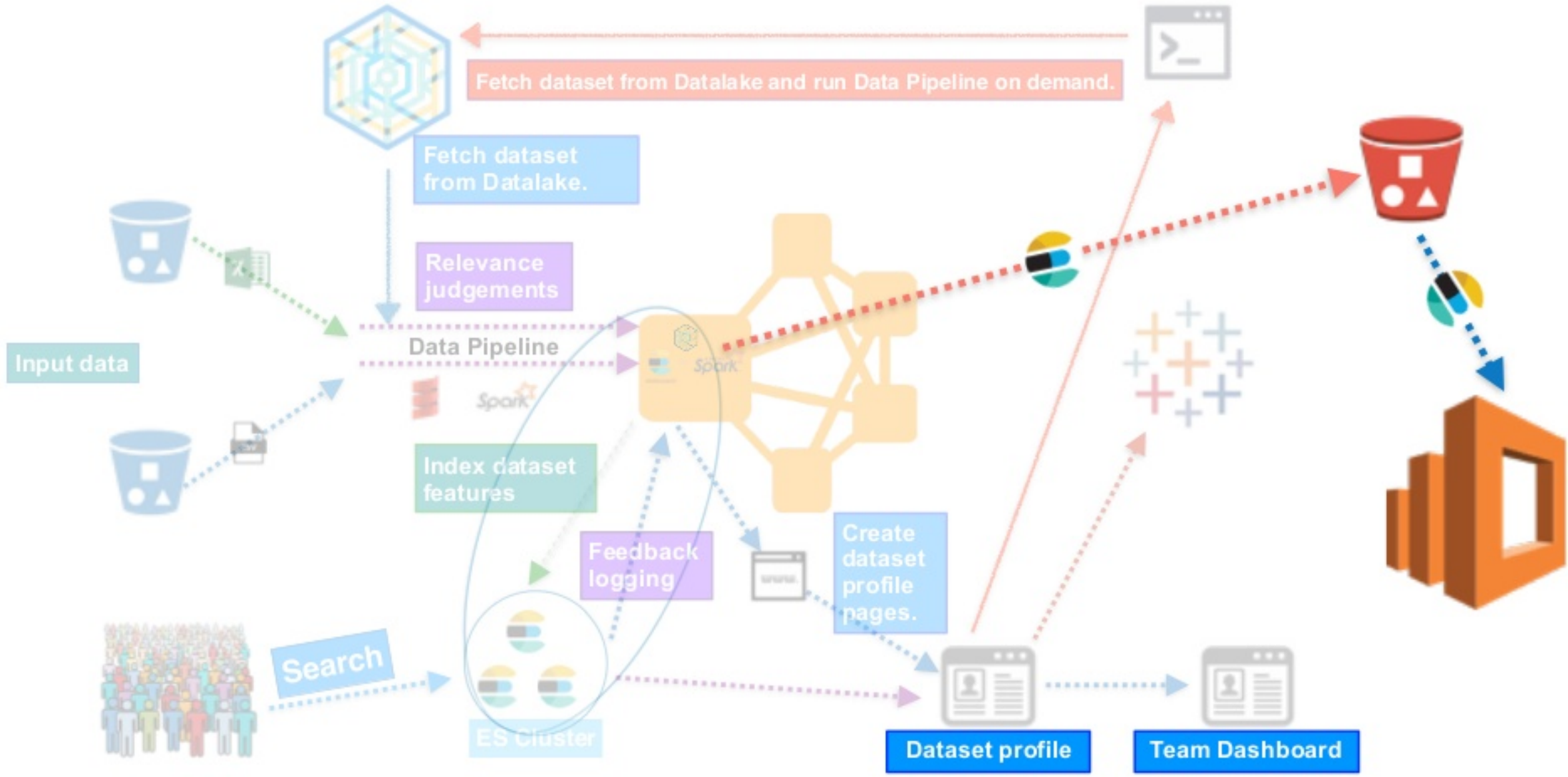


Organizing, Indexing and Ranking Datasets



How do you rank datasets?

Ranking datasets

- Extraction of "*relevance judgements*" can be built into data pipeline for specific datasets immediately after they are generated.

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  - Leveraged for training
  - And to bootstrap a dataset rank model
  - (*a posteriori* vs. post hoc (Halevy et al., 2016).)

Ranking datasets

- Click-through data provides implicit feedback useful to adjust initial relevance judgements.

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    - Leveraging click-through data on **dataset profile pages**.

Ranking datasets

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A posteriori vs. Post-hoc

- Alon et al (2016) advocate finding data in a *post-hoc* manner by collecting and aggregating metadata *after* datasets are created or updated.

- We propose a so-called "*a posteriori*" approach where metadata is *generated* as part of running pipelines using Spark.

A posteriori vs. Post-hoc

- Alon et al (2016) advocate indexing

after the fact

- We prefer indexing

immediately after the fact

immediately after the fact

Pros

- "*Relevance judgements*" can be extracted and leveraged to bootstrap a ranked dataset index.
  - In a feedback loop leveraging click-through data on Dataset profile pages.
- More granular metrics available to evaluate metadata regeneration.

immediately after the fact

Cons

- Offline model development is disconnected and only indirectly part of feedback using click-through data.
- Looking at trees instead of the forest.
- Need to replay indexing pipeline when things change (per data pipeline).

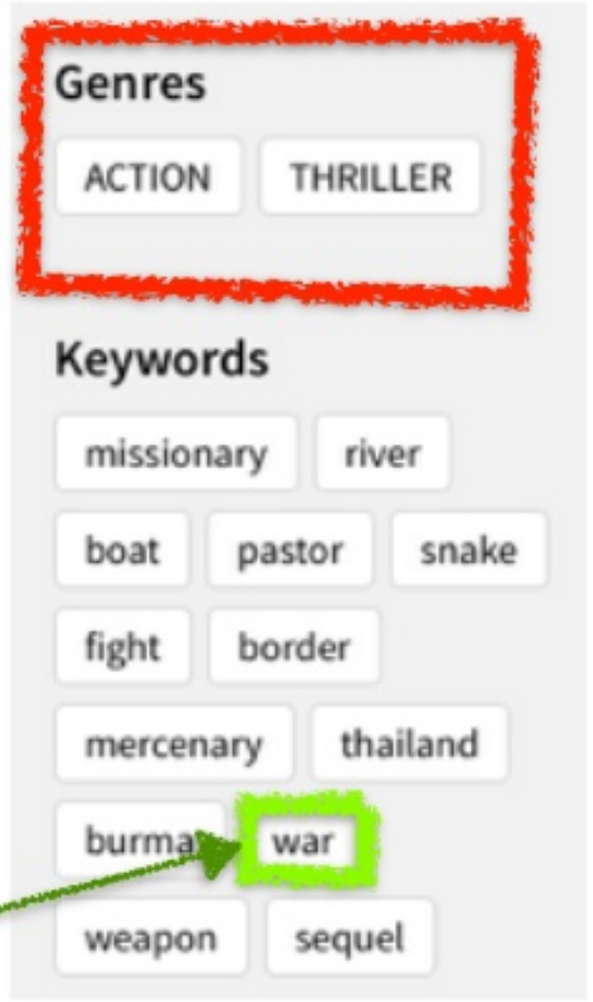
Demo!

Demo Scenario

- Movies represent datasets
- TMDB movie pages represent dataset profile pages.
- Marketing team (also called WAR team) interested in War movies (datasets).

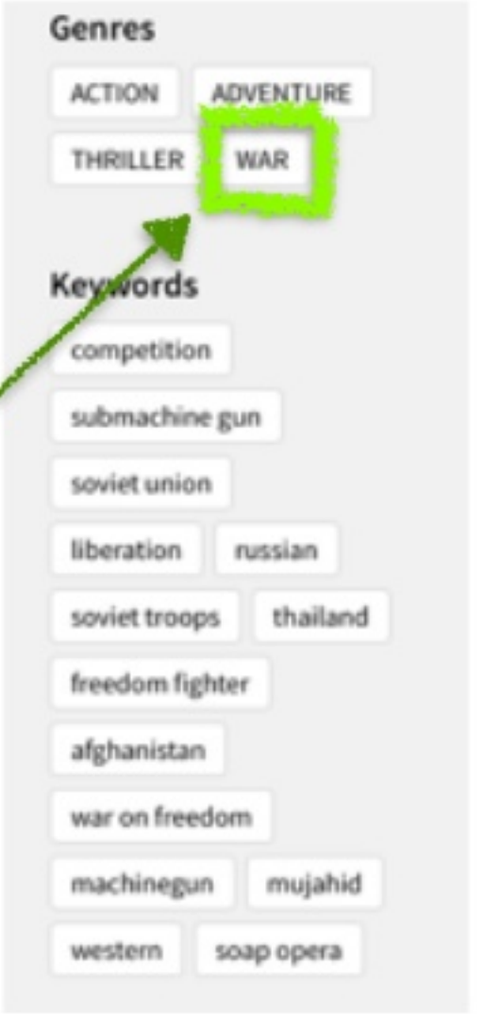
Movie 1

https://www.themoviedb.org/movie/7555-rambo



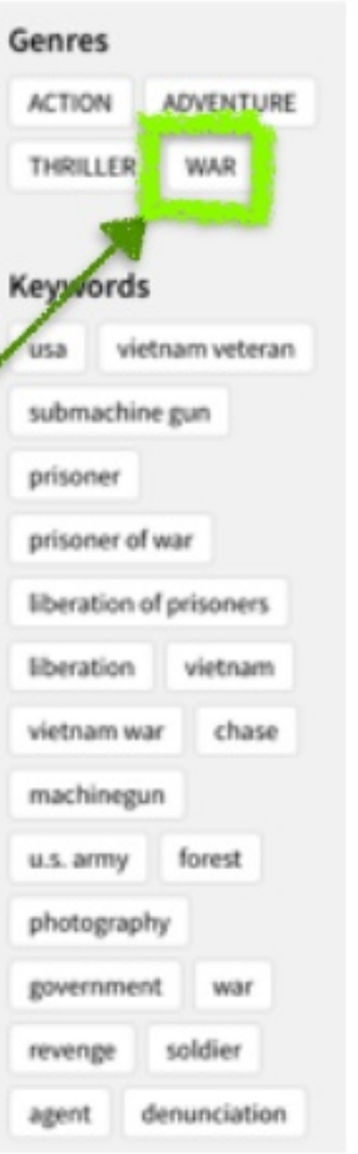
Movie 2

https://www.themoviedb.org/movie/1370-rambo-iii



Movie 3

https://www.themoviedb.org/movie/1369-rambo-first-blood-part-ii



judgement file

```
# grade (0-4)   queryid docId   title
#
# Add your keyword strings below, the feature script will
# Use them to populate your query templates
#
# qid:4: Drama
# qid:5: Comedy
# qid:6: War
# qid:8: Action
#
# https://sourceforge.net/p/lemur/wiki/RankLib%20File%20Format/
#
#
0       qid:6 # 7555
4       qid:6 # 1370
4       qid:6 # 1369
```

Rambo

Rambo III

Rambo: First Blood Part II

What have we seen?

- How to rank datasets on Elasticsearch using LTR.
- Extract relevance judgements immediately after datasets are generated in Spark.
- Demo: Dataset Search with Spark and Elasticsearch LTR.

Next Steps (1)

- **Describe Datasets in a structured schema.org way** using Data Catalog Vocabulary [2].

- **Build a knowledge graph** and use GraphX to extract insights. (Useful e.g. for column concept determination (Deng et al. 2013)).

- **Build topic models based on structured Datasets** using Glint to perform scalable topic model extraction in Spark (Jagerman and Eickhoff, 2016) [1].

[1] https://spark-summit.org/eu-2016/events/glint-an-asynchronous-parameter-server-for-spark/

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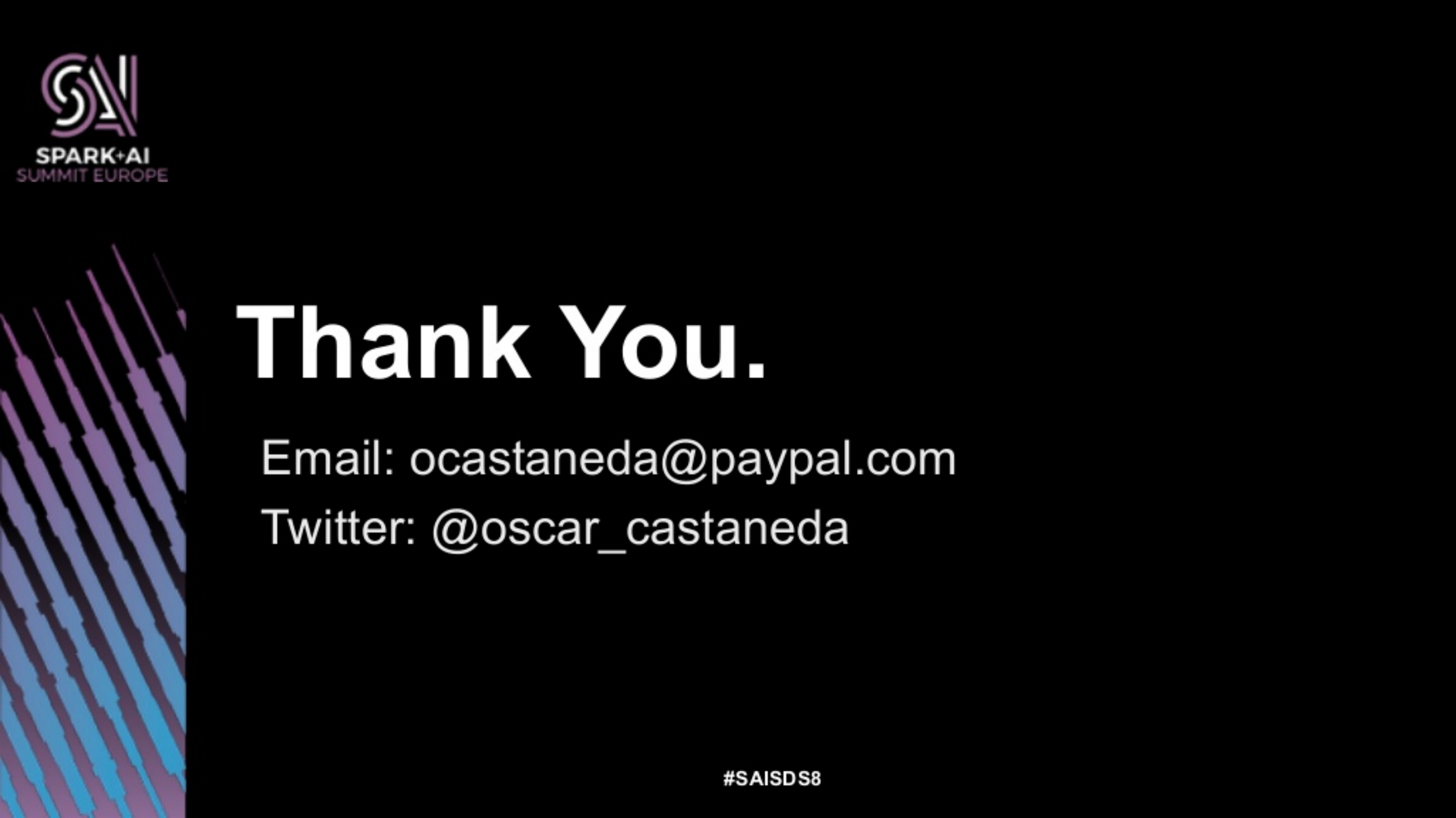
Q&A



Thank You.

Email: ocastaneda@paypal.com

Twitter: @oscar_castaneda