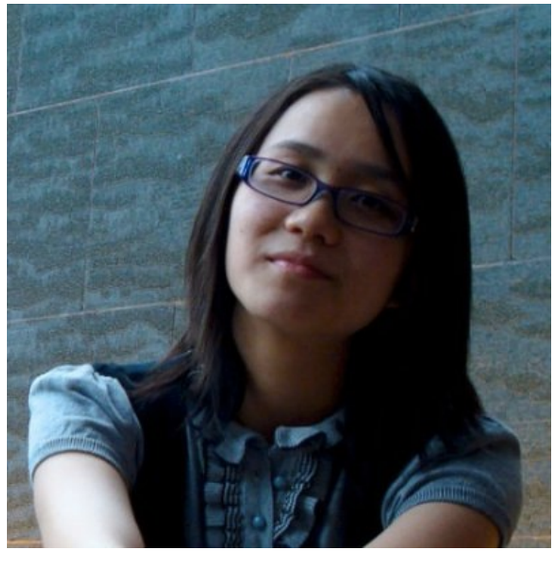
The ACM Conference Series on
Recommender Systems

RecSys 2015 Tutorial

Scalable Recommender Systems

Where Machine Learning
Meets Search!



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Index

1. Introduction

What to expect from this tutorial?

- The focus is on practical examples of how to implement scalable recommender systems using search and learning-to-rank (machine learning) techniques
- What it is not
  - Deep dive into any specific areas (Search, RecSys, Learning to rank, or Machine learning)
  - Algorithmic survey
  - Comparative Analysis

Finding commonalities

What is a recommendation?

Beyond rating prediction

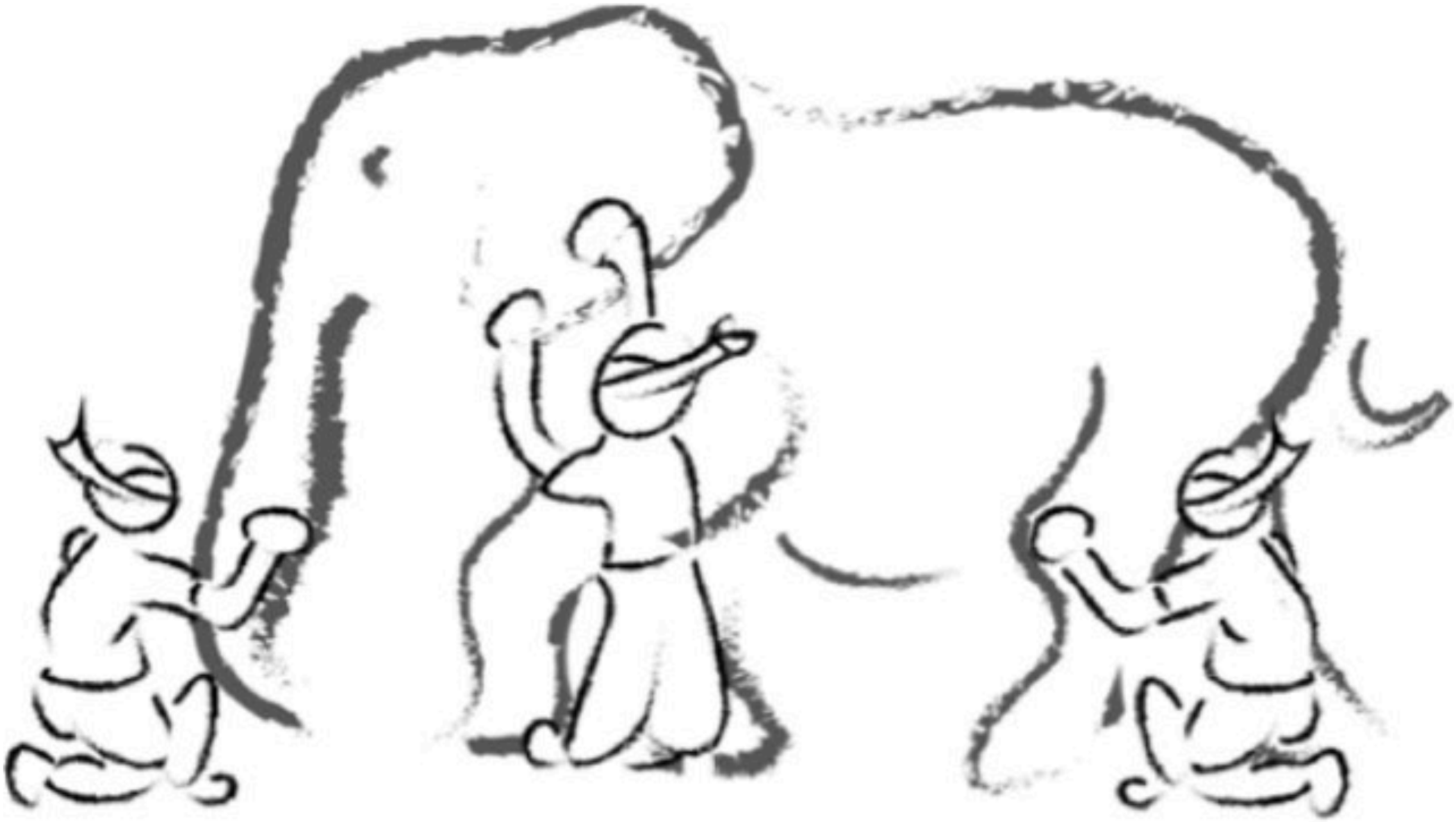


Image - "Everything Connects" (McGraw Hill, Feb 2014)

Paradigms of recommender systems

- Reduce information load by estimating relevance
- Ranking Approaches:
  - **Collaborative filtering**: “Tell me what is popular amongst my peers”
  - **Content Based**: “Show me more of what I liked”
  - **Knowledge Based**: “Tell me what fits my needs”
  - **Hybrid**

Model Type	Pros	Cons
Collaborative	• No metadata engineering effort • Serendipity of results • Learns market segments	• Requires rating feedback • Cold start for new users and new items
Content-based	• No community required • Comparison between items possible	• Content descriptions necessary • Cold start for new users • No serendipity
Knowledge-based	• Deterministic • Assured quality • No cold-start • Interactive user sessions	• Knowledge engineering effort to bootstrap • Static • Does not react to short-term trends

Scaling recommender systems is hard!

- *Millions of users*
- *Millions of items*
- *Cold start* for ever increasing size of catalog and new users added
- *Imbalanced Datasets* – power law distribution is quite common
- Many algorithms have not been fully tested at “Internet Scale”

2. Recommender System Problem as a Search Problem

Content-based methods inspired by IR

- **Rec Task**: Given a *user profile* find the best matching *items* by their *attributes*
- **Similarity calculation**: based on keyword overlap between user/items
  - Neighborhood method (i.e. nearest neighbor)
  - Query-based retrieval (i.e Rocchio's method)
  - Probabilistic methods (classical text classification)
  - Explicit decision models
- **Feature representation**: based on content analysis
  - Vector space model
  - TF-IDF
  - Topic Modeling

Search queries as content-based recommendations

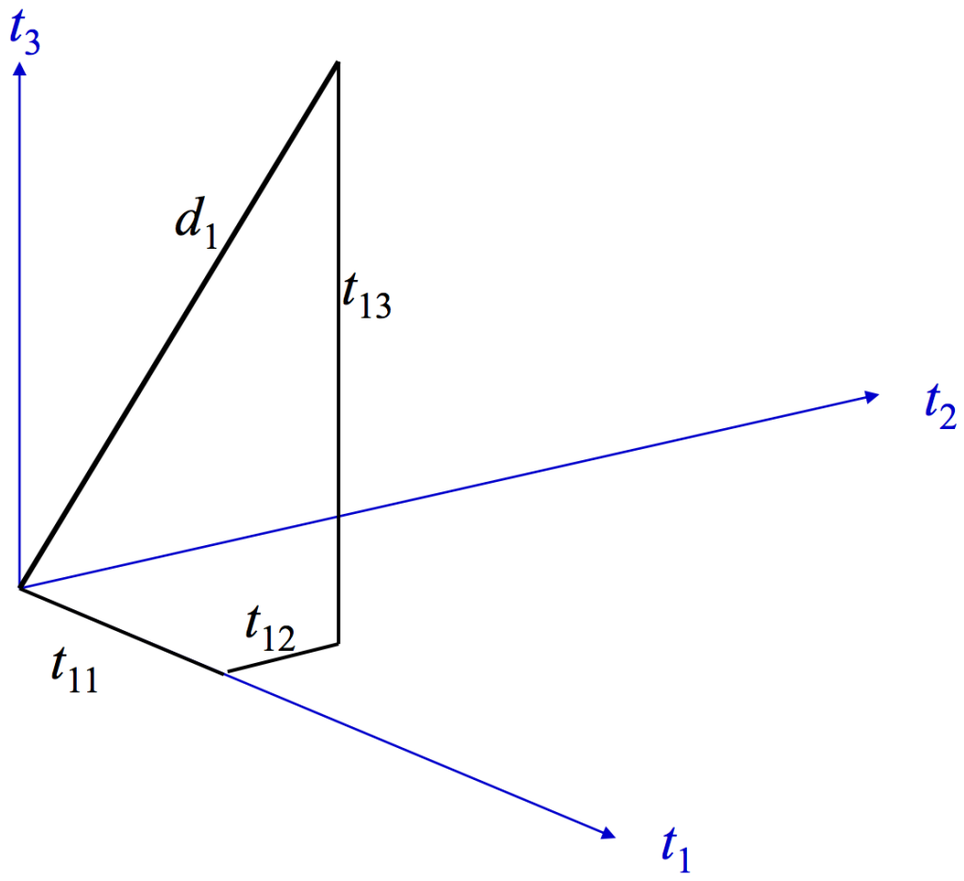
- Exact matching (Boolean)
  - Relevant or not relevant (no ranking)
- Ranking by similarity to query (Vector Space Model)
  - Text similarity: Bag of words, TF-IDF, Incidence Matrix

$$\text{score}(q,d) = \frac{\vec{V}(q) \cdot \vec{V}(d)}{|\vec{V}(q)||\vec{V}(d)|}.$$

- Ranking by importance (e.g. PageRank)

Content-based similarity measures

- Simple match $|Q \cap D|$
- Dice's Coefficient $2\dfrac{|Q \cap D|}{|Q| + |D|}$
- Jaccard's Coefficient $\dfrac{|Q \cap D|}{|Q \cup D|}$
- Cosine Coefficient $\dfrac{|Q \cap D|}{|Q|^{1/2} \times |D|^{1/2}}$
- Overlap Coefficient $\dfrac{|Q \cap D|}{\min(|Q|, |D|)}$



3D Term Vector Space

Knowledge-based methods inspired by IR

- **Rec Task**: Given *explicit recommendation rules* find the best matches between *user's requirements* and *item's* characteristics (i.e., which item should be recommended in which context?)
- **Similarity calculation**: based on constraint satisfaction problem and distance similarity requirements<->attributes
  - Conjunctive queries
  - Similarity metrics for item retrieval
- **Feature representation**: based on query representation
  - User defined preferences
  - Utility-based preferences
  - Conjoint analysis

Search queries as knowledge-based recommendations

- Constraint satisfaction problem (CSP) is a tuple (V,D,C)
  - V – set of variables
  - D – set of finite domains for V
  - C – set of constraints of possible V permutations
- Recommendation as CSP:
  (V,D,C) => (Vi *U* Vu, D, Cr *U* Ci *U* Cf *U* REQ)
  - Vu – user properties (possible user's requirements)
  - Vi – item properties
  - Cr – compatibility constraints (possible Vc permutations)
  - Ci – Item constraints (conjunction fully defines an item)
  - Cf – filter conditions (define Vu<->Vi relationships)
  - REQ – user's requirements

3. Introduction to Search and Information Retrieval

Search

Search is about finding specific things that are either known or assumed to exist, **Discovery** is about is about helping the user encounter what he/she didn't even know exists

Both Search and Discovery can be achieved through a query based data/information system.

Predicate Logic and Declarative Languages Rock!

Examples of query based systems

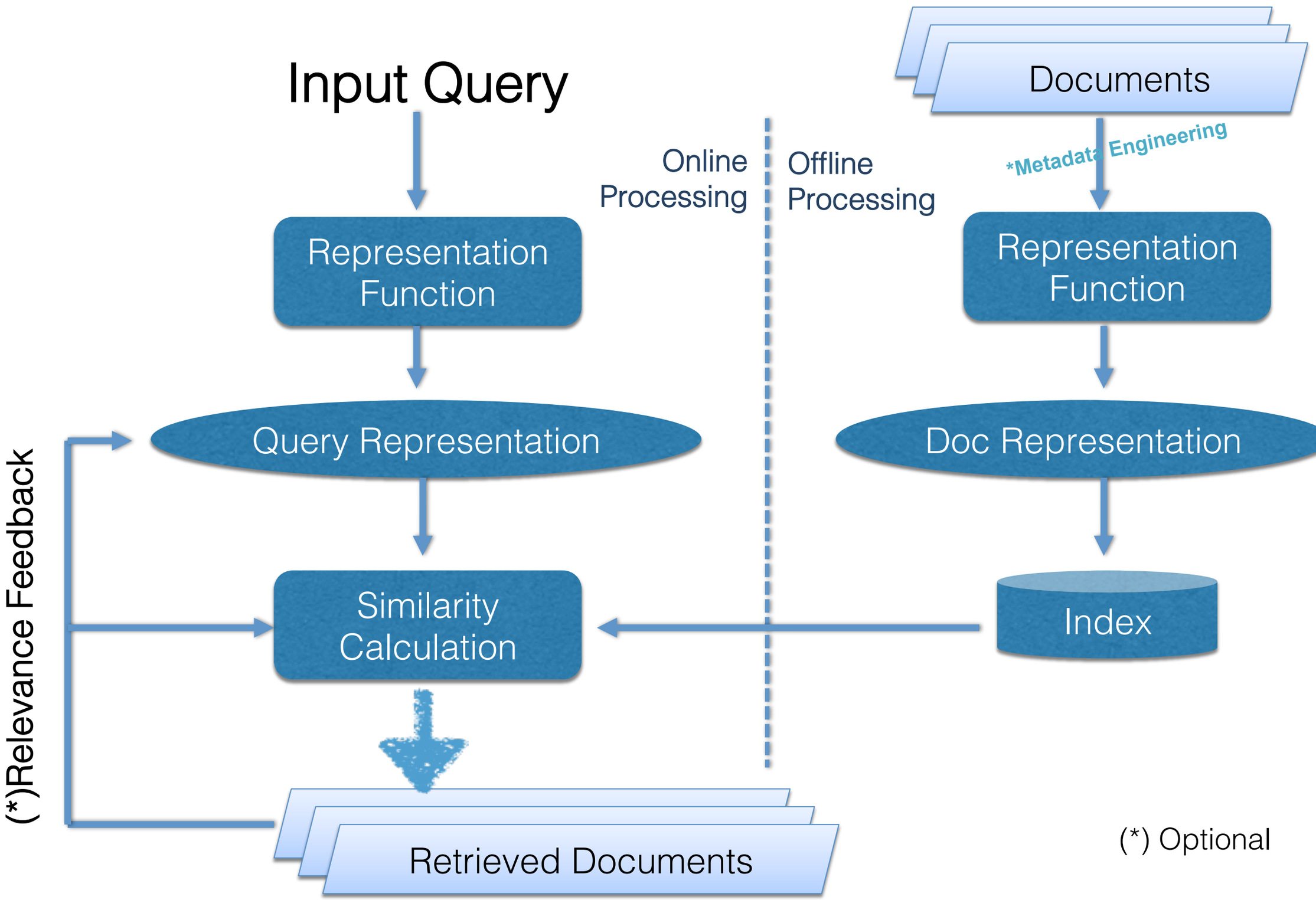
- Focused on Search
  - Search engines
  - Database systems
- Focus on Discovery
  - Recommender systems
  - Advertising systems

IR: The science behind search!

Information Retrieval (IR) is a query based on **data retrieval + relevance ranking** (scoring) usually applied to unstructured data (i.e. text documents and fields); often referred to as full-text or keyword search.

Have you heard of Bag-of-Words?
Vector Space Representation?
What about TF-IDF?

IR Architecture

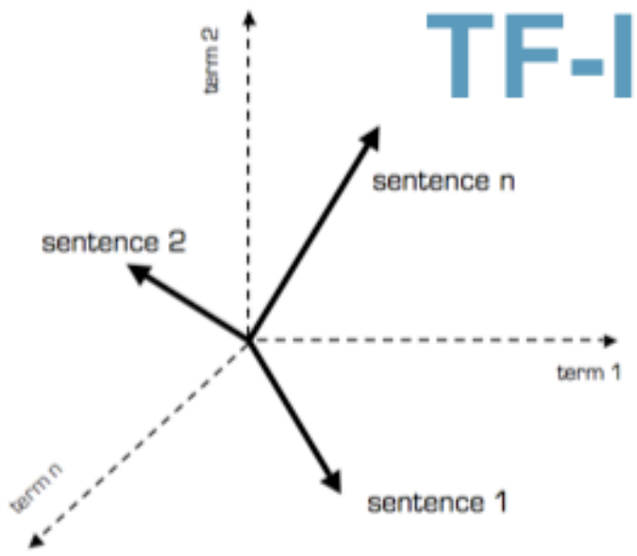


Retrieval Models

Model Type	Query Representation	Document Representation	Retrieval
Boolean	• Boolean expressions • Connected by AND, OR, NOT	• **Set** of keywords • Bag of words • Binary term weight	• Exact match • Binary relevance • No ranking
Vector Space Model	• Vector • Desired terms with optional weights	• Vectors • Bag of words with weight based on TF-IDF scheme	• Similarity score • Output documents are ranked • Relevance feedback support
Probabilistic	• Similarity with priors	• Document relevance	• Ranks documents in decreasing probability of relevance

Ranking in the Vector Space Model

TF-IDF



Language Model

P(optimization | search, engine) >>
P(walking | search, engine)

Probability Ranking Principle

P(R = 1 | d, q) or P(R = 0 | d, q)

Search Engines: the big hammer!

- Search engines are largely used to solve non-IR search problems, and here is why:
  - Widely available
  - Fast and scalable distributed systems
  - Integrates well with existing data stores (SQL and NoSQL)

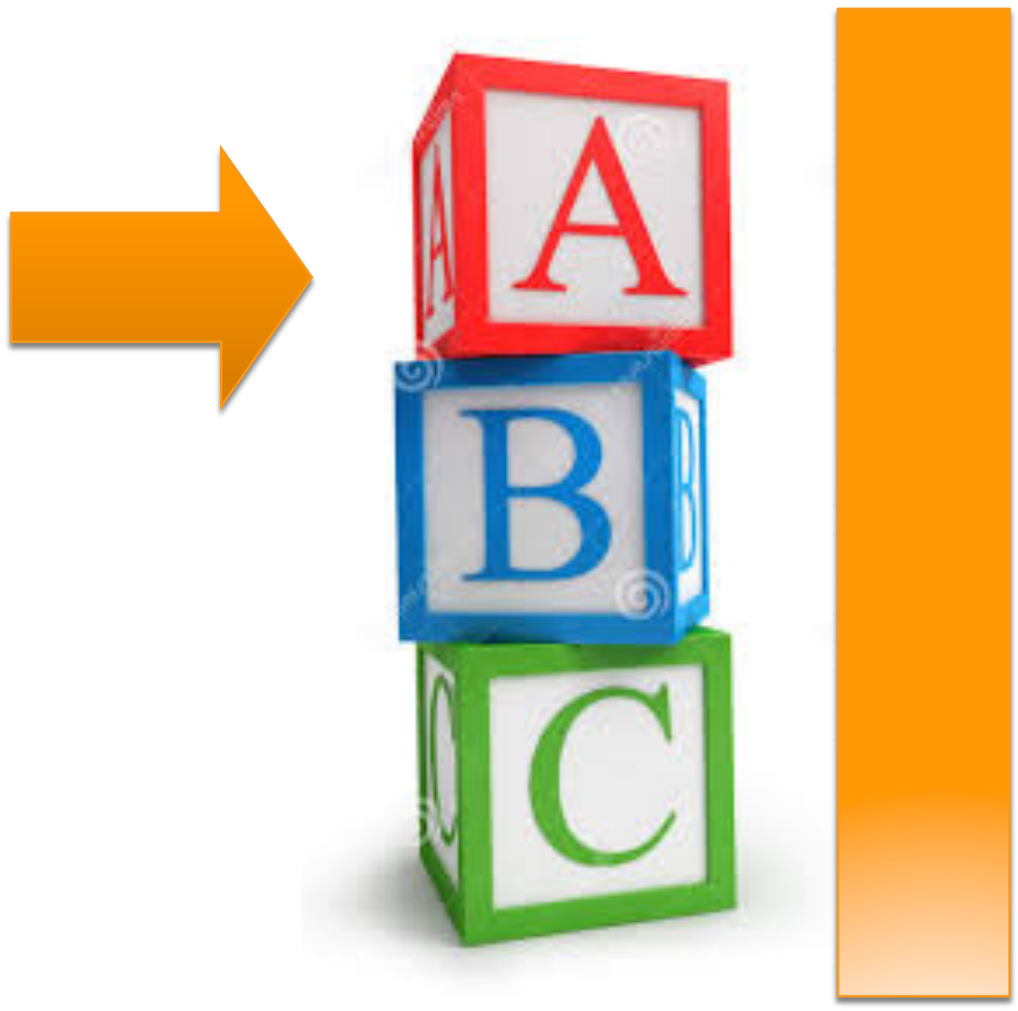
But are we using the right tool?

- Search Engines were originally designed for IR.
- More complex non-IR search/discovery tasks sometimes require a multi-phase, multi-system approach

Filter + Scoring: Two Phase Approach

Filter

Rank



Elasticsearch

- What is Elasticsearch?
  - Elasticsearch is an open-source search engine
  - Elasticsearch is written in Java
  - Built on top of Apache Lucene™
  - A distributed real-time document store where every field is indexed and searchable out-of-the box
  - A distributed search engine with real-time analytics
  - Has a plugin architecture that facilitates extending the core system
  - Written with NRT and cloud support in mind
  - Easy index, shard and replicas creation on live cluster
  - Has Optimistic Concurrency Control

Examples of scaling challenges

- More than 50 millions of documents a day
- Real time search
- Less than 200ms average query latency
- Throughput of at least 1000 QPS
- Multilingual indexing
- Multilingual querying

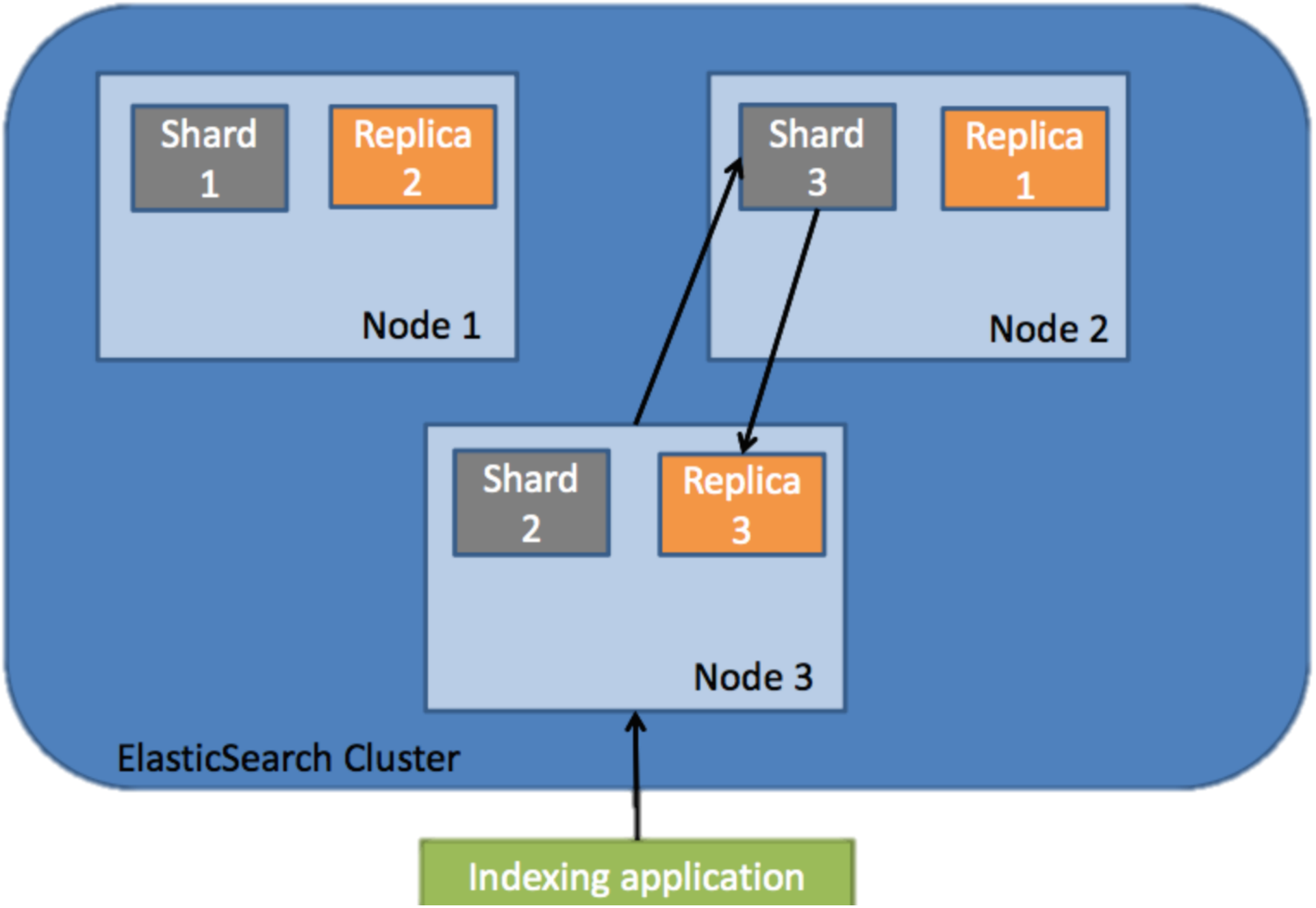
Who uses ES?

- Wikipedia
  - Uses Elasticsearch to provide full-text search with highlighted search snippets, and *search-as-you-type* and *did-you-mean* suggestions.
- The Guardian
  - Uses Elasticsearch to combine visitor logs with social -network data to provide real-time feedback to its editors about the public's response to new articles.
- Stack Overflow
  - Combines full-text search with geo-location queries and uses more-like-this to find related questions and answers.
- GitHub
  - Uses Elasticsearch to query 130 billion lines of code.

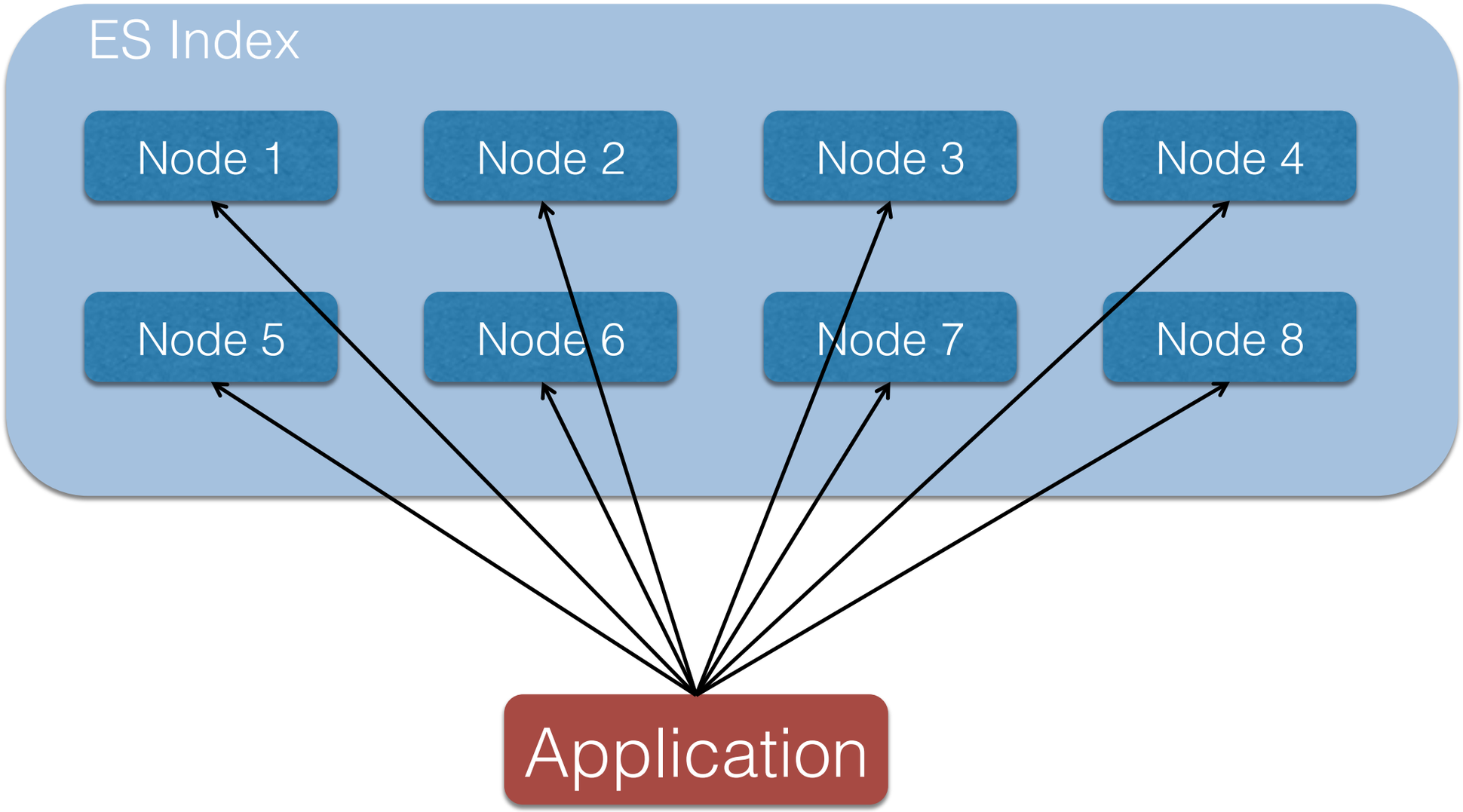
How ES scales?

- Sharding and Replicas
  - Several indices (at least one index for each day of data)
  - Indices divided into multiple shards
  - Multiple replicas of a single shard
  - Real-time, synchronous replication
  - Near-real-time index refresh (1 to 30 seconds)

Indexing the data



Querying ES


ES Index
Node 1
Node 2
Node 3
Node 4
Node 5
Node 6
Node 7
Node 8
Application

Using Search Engines for RS

- Its not just about rating prediction and ranking
  - Business filtering logic
    - Age restrictions
    - Catalog navigation context (e.g. e-commerce)
    - Promotional materials
  - Low latency and scale
    - SLAs on response times including query, responses and presentation
    - Actual time for computing recommendations is just a small fraction of total allocated time

Stacking things up

Offline

Online

Query Generation and Contextual Pre-filtering

Model Building

Retrieval

Index Building

Contextual Post Filtering

Data Analytics

Ranking

Visualization / UI

Experimentation

Data/Events Collections

Ranking in Elasticsearch

```
score(q,d)  =  ❶
           queryNorm(q)  ❷
         · coord(q,d)    ❸
         · Σ (           ❹
             tf(t in d)   ❺
           · idf(t)²      ❻
           · t.getBoost() ❼
           · norm(t,d)    ❽
           ) (t in q)    ❹
```

❶ `score(q,d)` is the relevance score of document `d` for query `q`.

❷ `queryNorm(q)` is the *query normalization* factor (new).

❸ `coord(q,d)` is the *coordination* factor (new).

❹ The sum of the weights for each term `t` in the query `q` for document `d`.

❺ `tf(t in d)` is the term frequency for term `t` in document `d`.

❻ `idf(t)` is the inverse document frequency for term `t`.

❼ `t.getBoost()` is the *boost* that has been applied to the query (new).

❽ `norm(t,d)` is the field-length norm, combined with the index-time field-level boost, if any. (new).

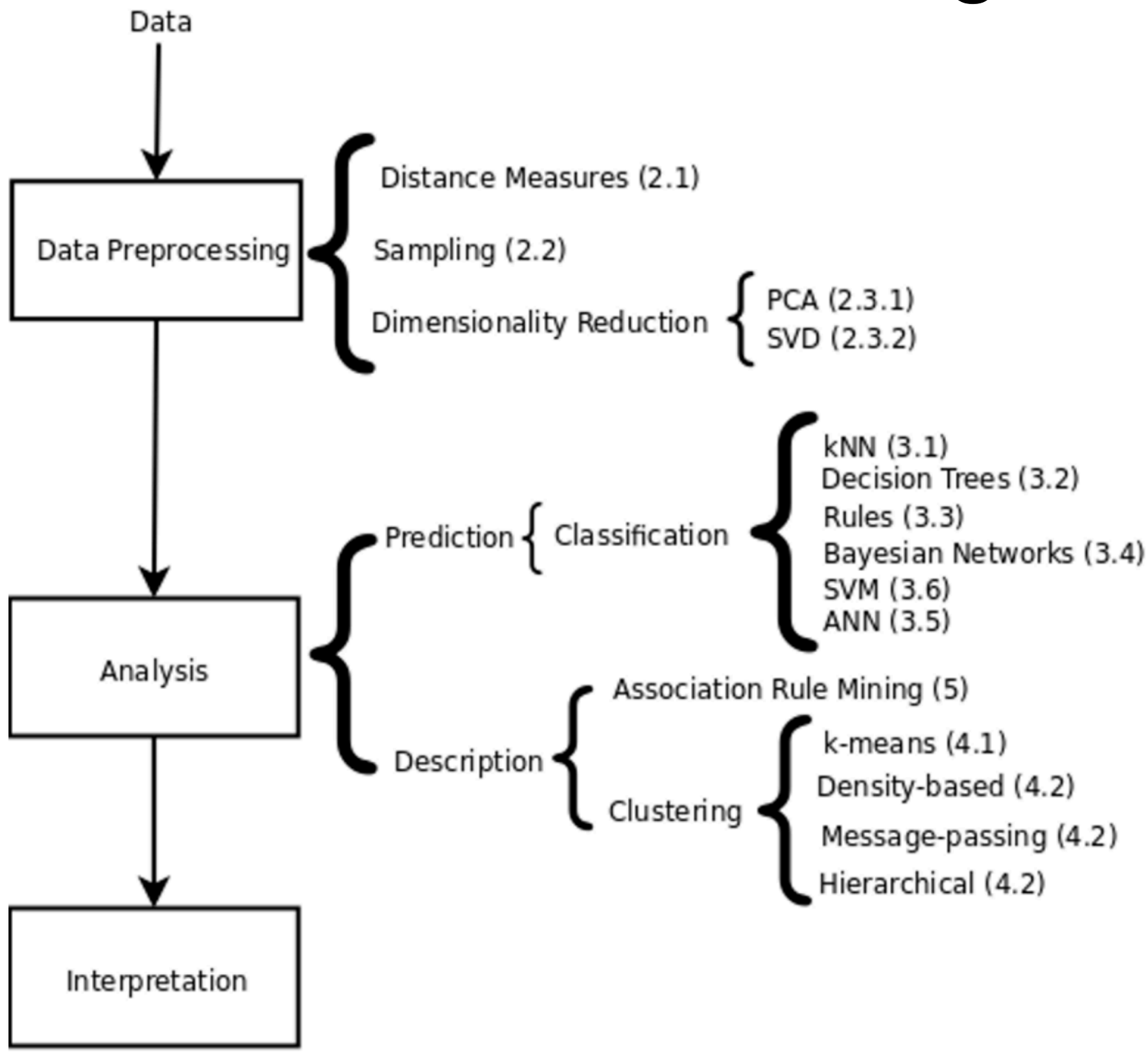
4. Overview of Machine Learning Techniques for Recommender Systems

Machine Learning

Machine Learning in particular *supervised learning* refer to techniques used to learn how to classify or score previously unseen objects based on a training dataset

Inference and Generalization are the Key!

Recommendations as data mining



Amatriain, Xavier, et al. "Data mining methods for recommender systems." Recommender Systems Handbook. Springer US, 2011. 39-71.

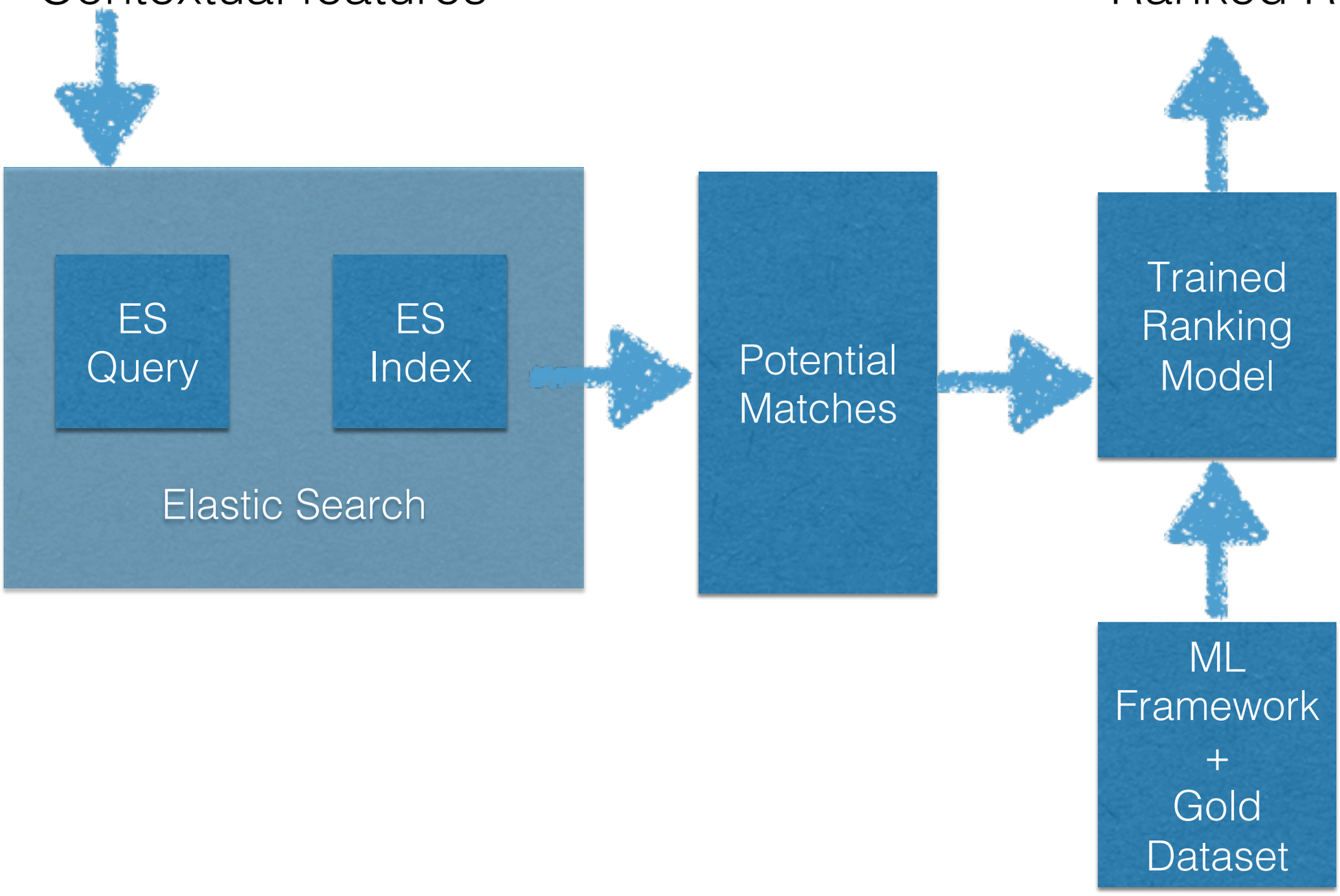
Learning to rank

- Formulate the problem as standard supervised learning
- Training data can be cardinal or binary
- Various approaches:
  - Pointwise: Typically approximated by regression
  - Pairwise: Approximated via binary classifier
  - Listwise: Directly optimize whole list (difficult!)
- A trick with ES is to include raw scores returned by ES into the feature vector

Learning to rank with ES

Input:
Contextual features

Output:
Ranked Results



Web scale ML challenges

- Massive amount of examples
- Billions of features
- Big models don’t fit in a single machine’s memory
- Variety of algorithms that need to be scaled up

A Note of Caution….

"Invariably, ***simple models*** *and* ***a lot of data*** *trump more elaborate models* **based on less data**."

Alon Halevy, Peter Norvig, and Fernando Pereira, Google

http://static.googleusercontent.com/external_content/untrusted_dlcp/research.google.com/en//pubs/archive/35179.pdf

Scalability in Machine Learning

- Distributed systems – *Fault tolerance, Throughput vs. latency*
- Parallelization Strategies – *Hashing, trees*
- Processing – *Map reduce variants, MPI, graph parallel*
- Databases – *Key/Value Stores, NoSQL*

What is Spark?

Fast, expressive cluster computing system

BlinkDB
approx queries

Spark SQL
structured data

Spark Streaming
real-time

MLlib
machine learning

GraphX
graph Analytics

Spark Core

What is Spark?

- Work on distributed collections like local ones
- RDD:
  - Immutable
  - Parallel transforms
  - Resilient and configurable persistence
- Operations
  - Transforms: Lazy operations (map, filter, join,…)
  - Actions: Return/write results (collect, save, count,…)

ML Software Framework: Spark MLlib

- Subproject with ML primitives
- Building blocks (as a framework vs. library)
  - Large scale statistics
  - Classification
  - Regression
  - Clustering
  - Matrix factorization
  - Optimization
  - Frequent pattern mining
  - Dimensionality reduction

What is ML-Scoring?

- Creates an Elastic Search (ES) document index of instances
- Trains a supervised learning ML model from a dataset of instances + labels
- Generate an Elasticsearch plugin that uses the trained ML model to score documents at query time

- A
-

An Open Source POC!

Remember the elephant?

Offline

Online

Query Generation and Contextual Pre-filtering

Model Building

Retrieval

Index Building

Contextual Post Filtering

Data Analytics

Ranking

Visualization / UI

Experimentation

Data/Events Collections

Simplifying the Stack!

Offline

Online

Query Generation and Contextual Pre-filtering

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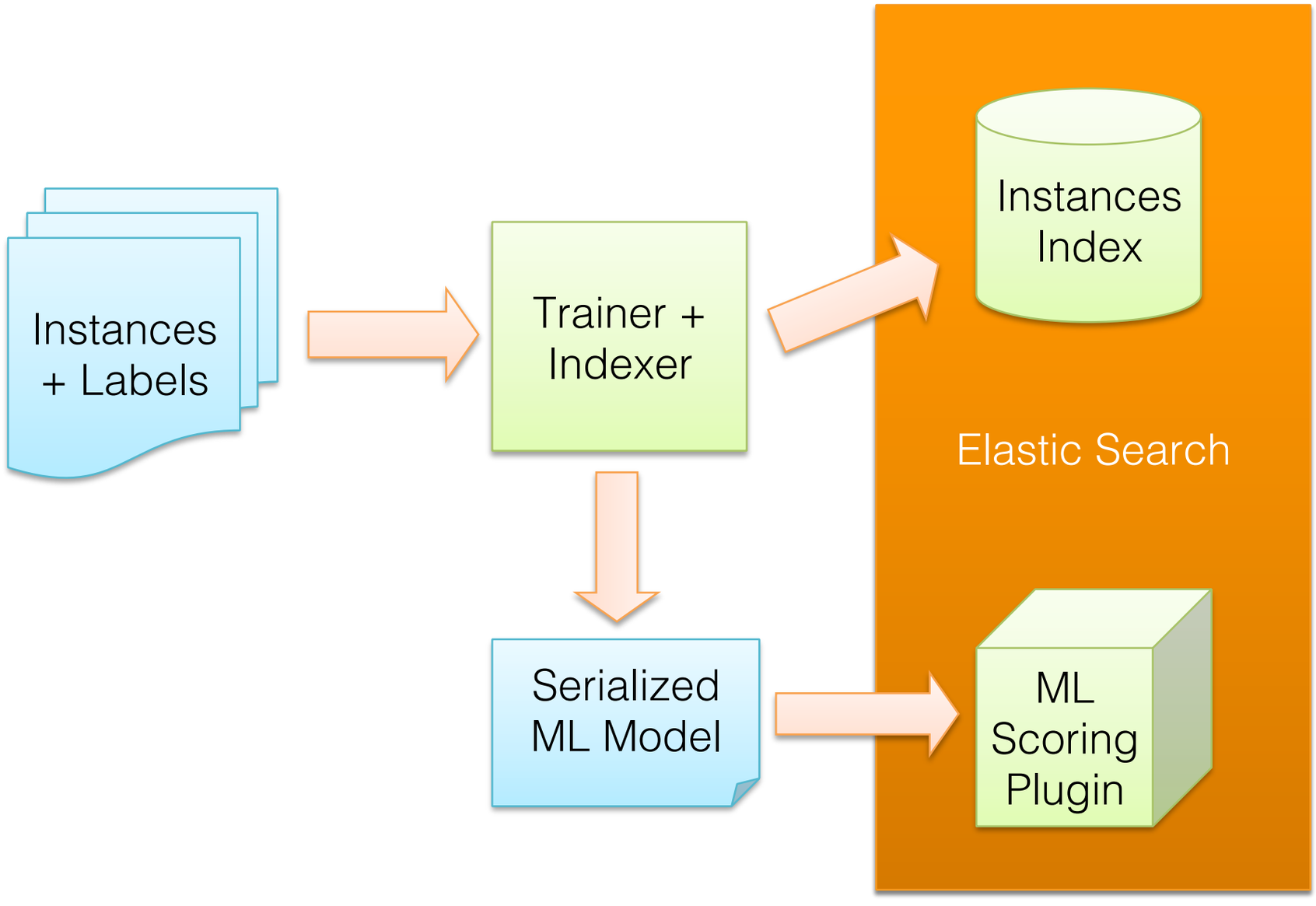
ML-Scoring Architecture



5. Re-writing the ranking function

Using ML-Scoring

- Creating an ES Index
- Boolean queries
- More-Like-This queries
- Built-in scoring functions
- Scoring script
- Scoring plugin
- ML-Score evaluator using Spark
- ML-Score query

Creating an Index in ES

```
POST /my_movie_catalog/movies/_bulk
{ "index": { "_id": 1 }}
{ ”genre" : “Documentary”, ”productID" : "XHDK-A-1293-#fJ3" , “title” : “Olympic Sports”, “content” : “Olympic greateness…“, price” : 20}
{ "index": { "_id": 2 }}
{ ”genre" : “Sports”, ”productID" : "KDKE-B-9947-#kL5", “title” : “NY Yankees: Winning the World Series”, , “content” : “There is no better team than the NY…“ “price” :20}
{ "index": { "_id": 3 }}
{ ”genre" : “Action”, “productID" : "JODL-X-1937-#pV7",”title” : “Rambo III”, , “content” : “Sylvester Stallone is evermore…“ “price” : 18}
{ "index": { "_id": 4 }}
{ ”genre" : “Children”, ”productID" : "QQPX-R-3956-#aD8", “title” : “Fairy Tale”, , “content” : “Once upon a time…“, “price” : 30}
```

Boolean queries

- SQL representation

SELECT movie

FROM movies

WHERE (price = 20 OR productID = "XHDK-A-1293-#fJ3")

AND (price != 30)

- ES DSL

```
GET /my_movie_catalog/movies/_search
    {
       "query" : {
          "filtered" : {
             "filter" : {
                "bool" : {
                  "should" : [
                     { "term" : {"price" : 20}},
                     { "term" : {"productID" : "XHDK-A-1293-#fJ3"}}
                  ],
                  "must_not" : {
                     "term" : {"price" : 30}
…
```

Content based similarity queries (MLT)

- The More Like This Query (MLT Query) finds documents that are "like" a given set of documents. In order to do so, MLT selects a set of representative terms of these input documents, forms a query using these terms, executes the query and returns the results.

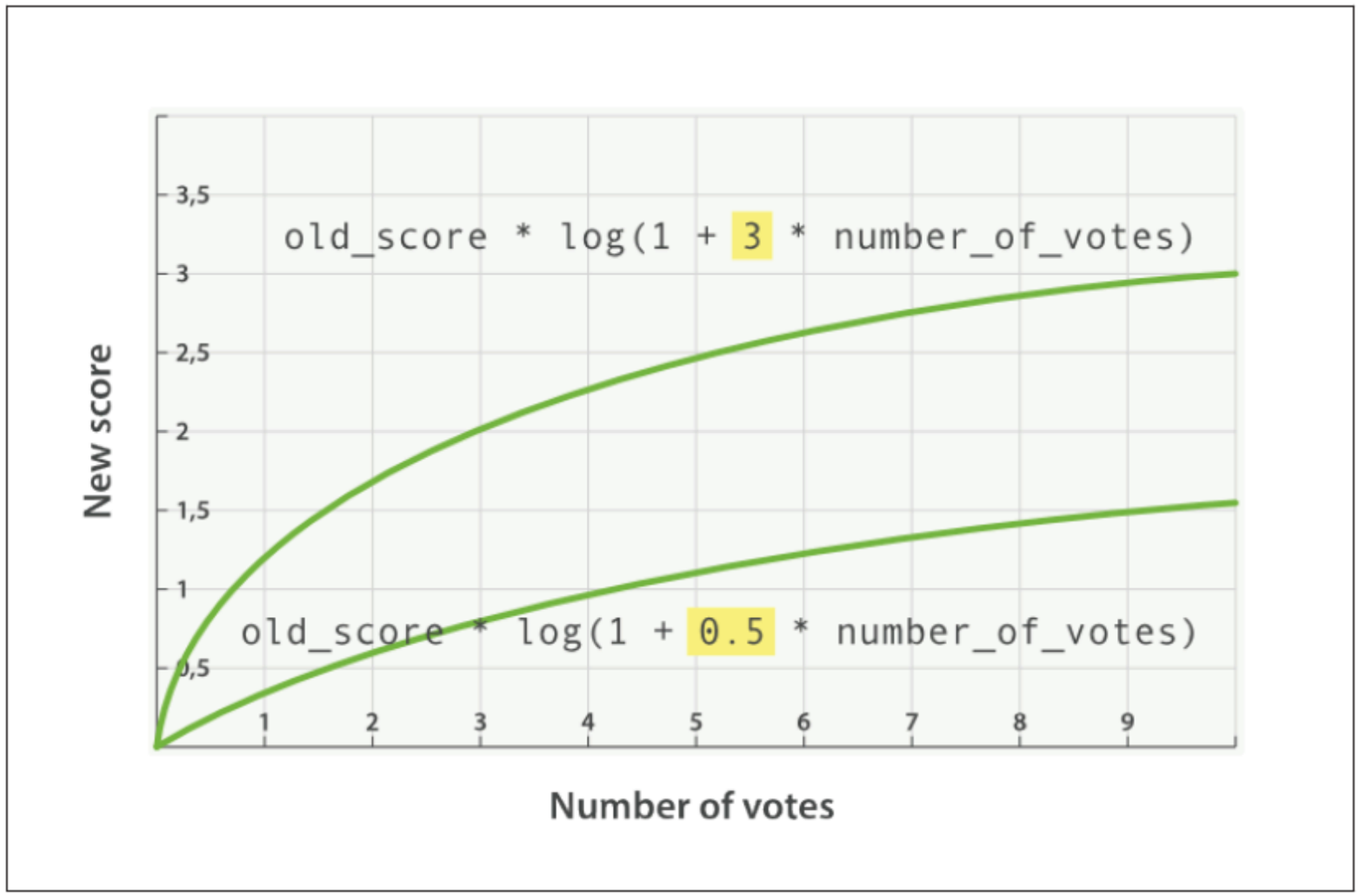
```
{
    "more_like_this" : {
        "fields" : ["title", "description"],
        "like_text" : "Once upon a time",
        "min_term_freq" : 1,
        "max_query_terms" : 12
    }
}
```

Similar to a given document

```
{
    "more_like_this" : {
        "fields" : ["title",
"description"],
        "docs" : [
        {
            "_index" : "imdb",
            "_type" : "movies",
            "_id" : "1"
        },
        {
            "_index" : "imdb",
            "_type" : "movies",
            "_id" : "2"
        }],
        "min_term_freq" : 1,
        "max_query_terms" : 12
    }
}
```

Built-in functions

- Suppose we want to boost movies by popularity (base-line of many RS)

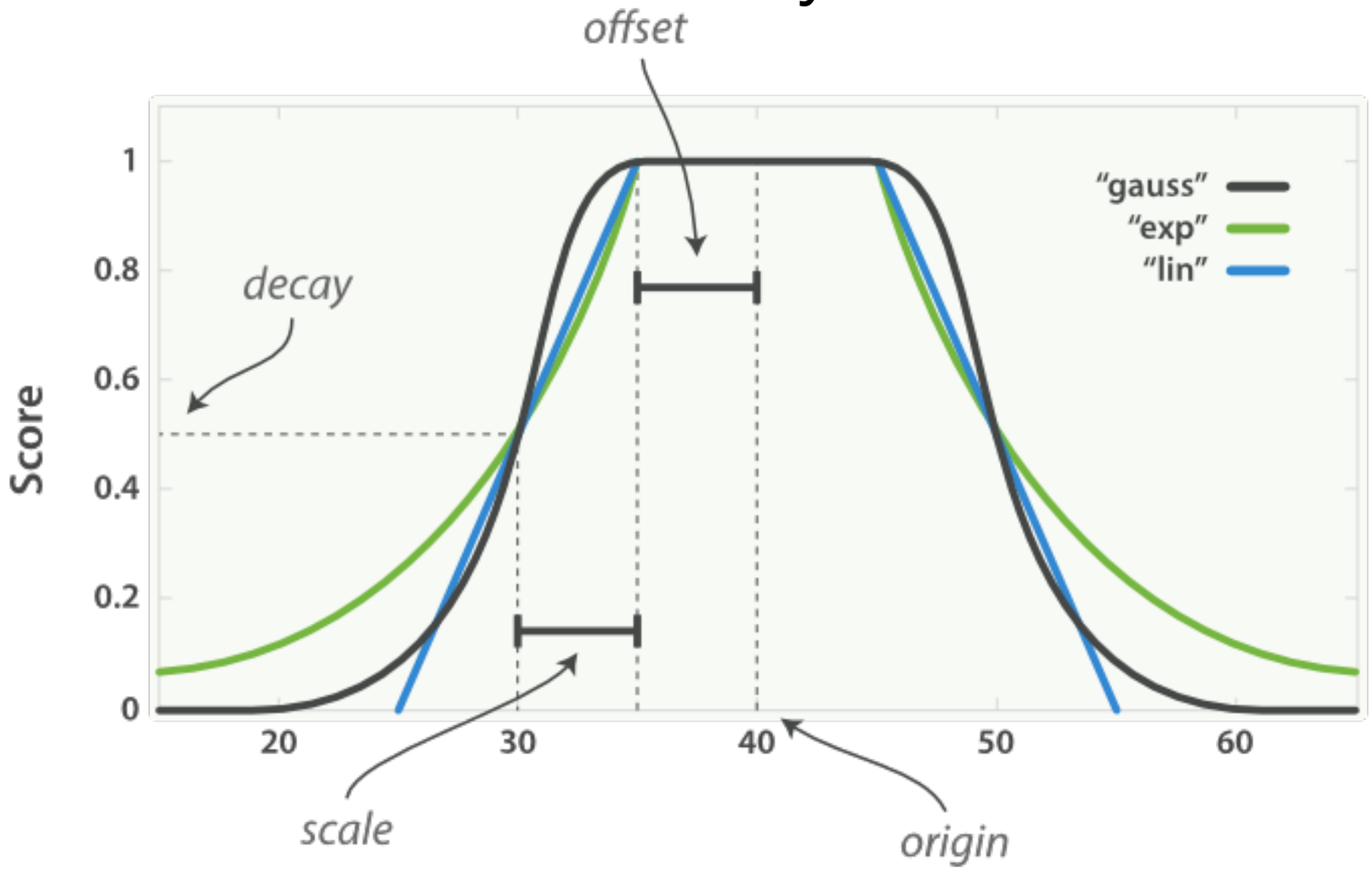


Popularity-based boosting

```
GET /my_movie_catalog/movies/post/_search
{
"query": {
   "function_score": {
      "query": {
         "multi_match": {
         "query": "popularity",
         "fields": [ "title", "content" ]
         }
      },
      "field_value_factor": {
         "field": "votes",
         "modifier": "log1p"
         }
      }
   }
}
```

Geo-Location

- Suppose we want to build a location-aware recommender system



Decay functions

- Supported decay functions
  - Linear
  - Gauss
  - Exp
- Also supported
  - random_score

```
GET /_search
{
"query": {
"function_score": {
    "functions": [
    {
        "gauss": {
        "location": {
            "origin": { "lat": 51.5, "lon": 0.12 },
            "offset": "2km",
            "scale": "3km"
        }
    }
},
{
    "gauss": {
    "price": {
        "origin": "50",
        "offset": "50",
        "scale": "20"
    }
},
"weight": 2
…
```

ES scoring script

- Trickier pricing and margin based scoring

```
if (price < threshold) {
   profit = price * margin
} else {
   profit = price * (1 - discount) * margin
}
return profit / target
```

ES Scoring Script

```
GET /_search
{
"function_score": {
 "functions": [
   { ...location clause... },
   { ...price clause... },
   {
    "script_score": {
       "params": { "threshold": 80, "discount": 0.1, "target":
10 },
       "script": "price = doc['price'].value; margin =
doc['margin'].value; if (price < threshold) { return price *
margin / target };return price * (1 - discount) * margin /
target; "}
    …
```

Limitations of ranking using ES practical scoring function

- Stateless computation
- Meant primarily for text search
- Hard to represent context and history
- Limited complexity (simple math functions only)
- Nevertheless, original score should not be discarded as it may become handy!

Scoring plugin in ES

```
public class PredictorPlugin extends AbstractPlugin {

   @Override
   public String name() {
    return getClass().getName();
   }

   @Override
   public String description() {
    return "Simple plugin to predict values.";
   }

   public void onModule(ScriptModule module) {
    module.registerScript(
       PredictorScoreScript.SCRIPT_NAME,
       PredictorScoreScript.Factory.class);
   }
}
```

ML-Scoring evaluator using Spark

```
class SparkPredictorEngine[M](val readPath: String, val spHelp:
SparkModelHelpers[M]) extends PredictorEngine {

  private var _model: ModelData[M] = ModelData[M]()

  override def getPrediction(values: Collection[IndexValue]) = {
   if (_model.clf.nonEmpty) {
     val v = ReadUtil.cIndVal2Vector( values, _model.mapper)
     _model.clf.get.predict(v)
   } else {
     throw new PredictionException("Empty model");
   }
  }

  def readModel() = _model = spHelp.readSparkModel(readPath)

  def getModel: ModelData[M] = _model

  …
```

ML-Scoring query

```
{
  "query": {
    "function_score": {
      "query": {
        "match_all": {}
      },
      "functions": [
        {
          "script_score": {
            "script": "search-predictor",
            "lang": "native",
            "params": {}
          }
        }
      ],
    "boost_mode": "replace"
    }
  }
}
```

https://github.com/sdhu/elasticsearch-prediction

Potential issues

- Performance
  - It may be a problem if the search space is very large and/or the computation to intensive
- Operations
  - Code running on a key infrastructure
  - Versioning and binary compatibility

Summary

- Importance of the whole picture – RS seen from the lenses of the whole elephant
- RS research is a new field in comparison to IR
- Scalability is hard! Why not learn from all of RS's cousins:
  - Search
  - Distributed systems
  - Databases
  - Machine learning
  - Content analysis
  - …
- Bridging the gap between research and engineering is an ongoing effort

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