SIGMOD 2018

Automatically Leveraging MapReduce Frameworks for Data-Intensive Applications

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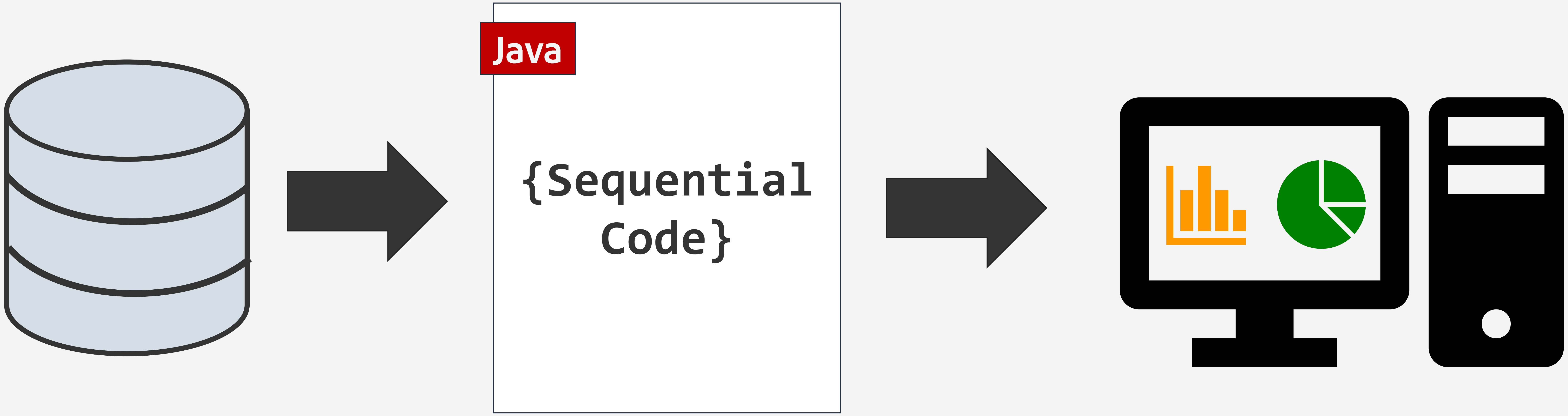
UW DB

PLSE

Why translate sequential code to MapReduce?

Optimizing Existing Applications



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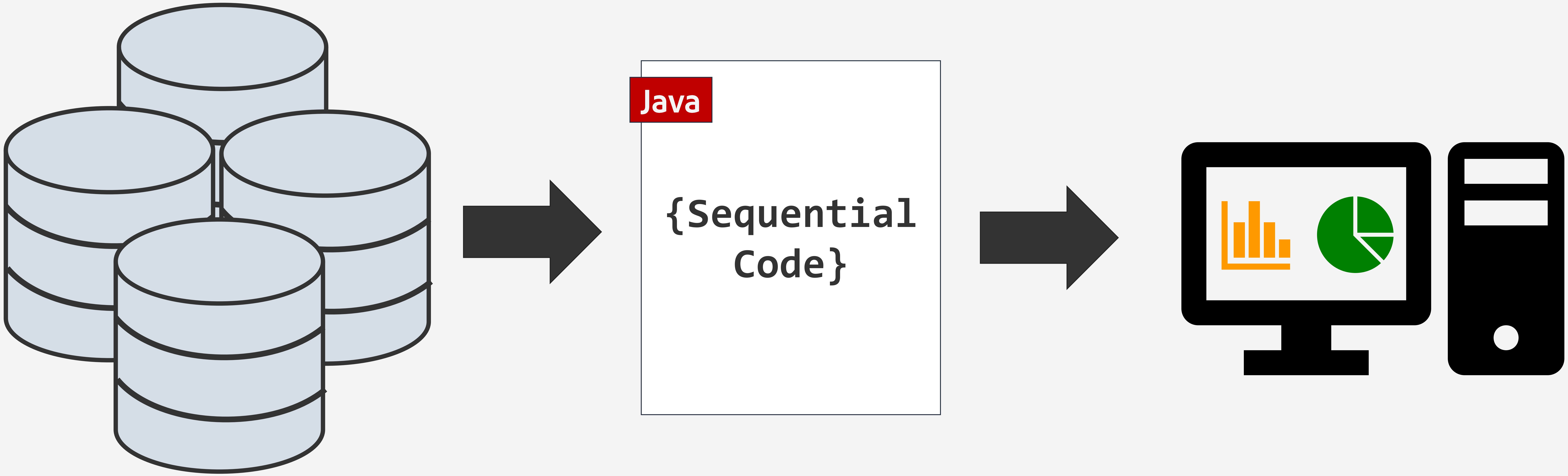

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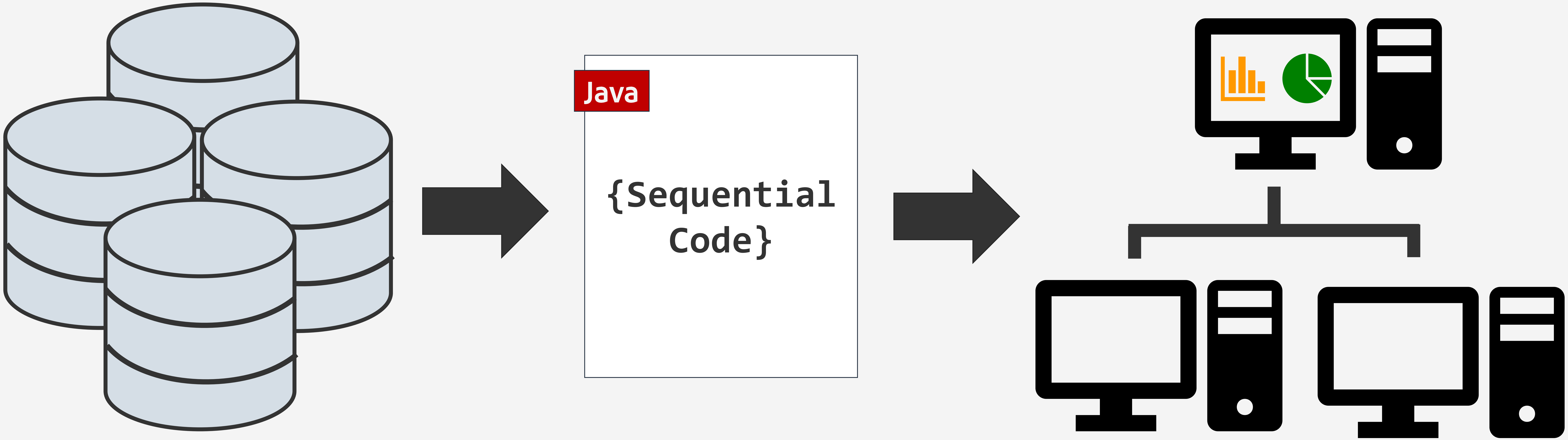

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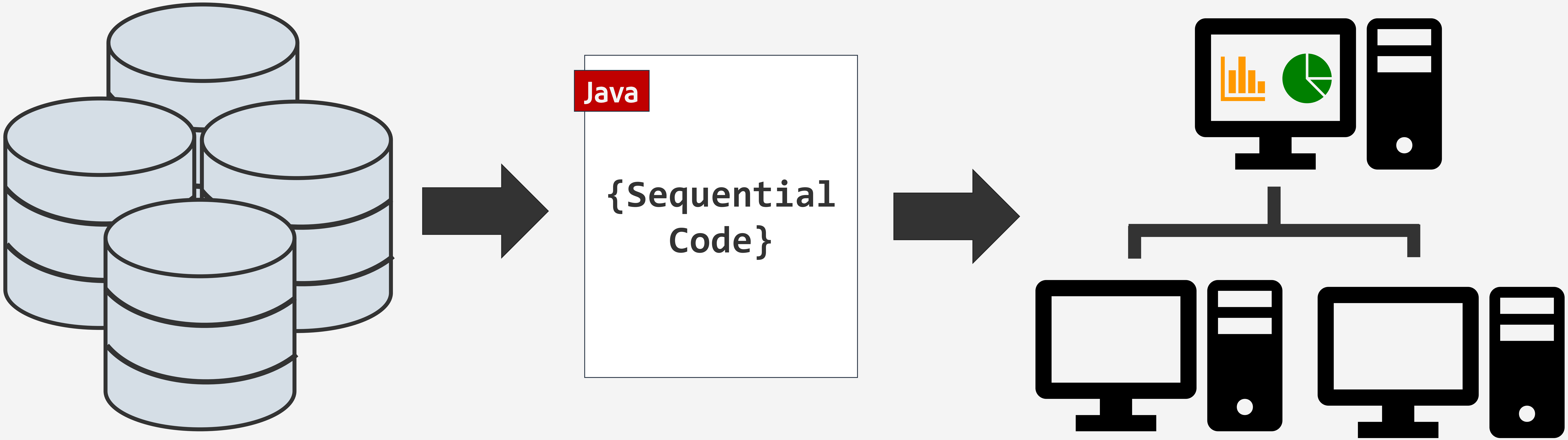

Flink Spark hadoop

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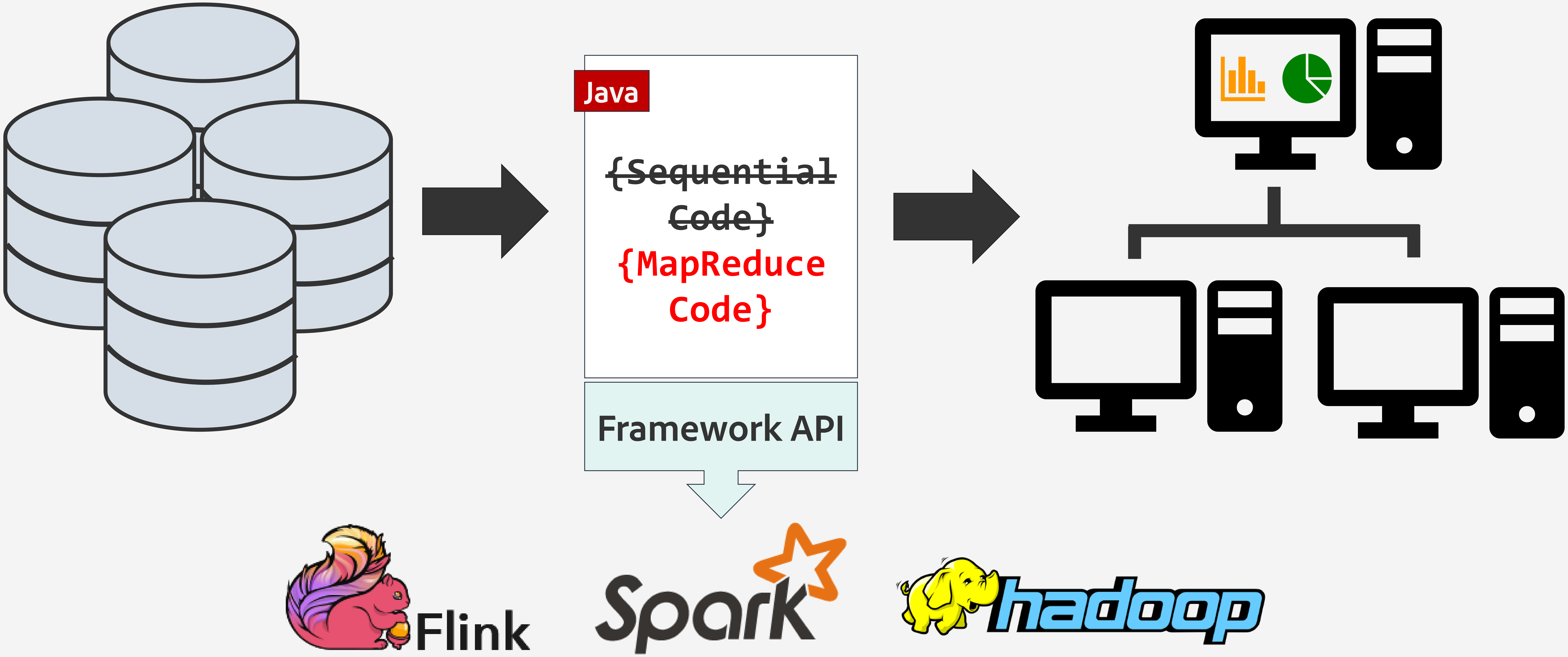


Option 1: Manual Re-write

- Recurring
- Error-prone
- Tedious
- Requires Expertise

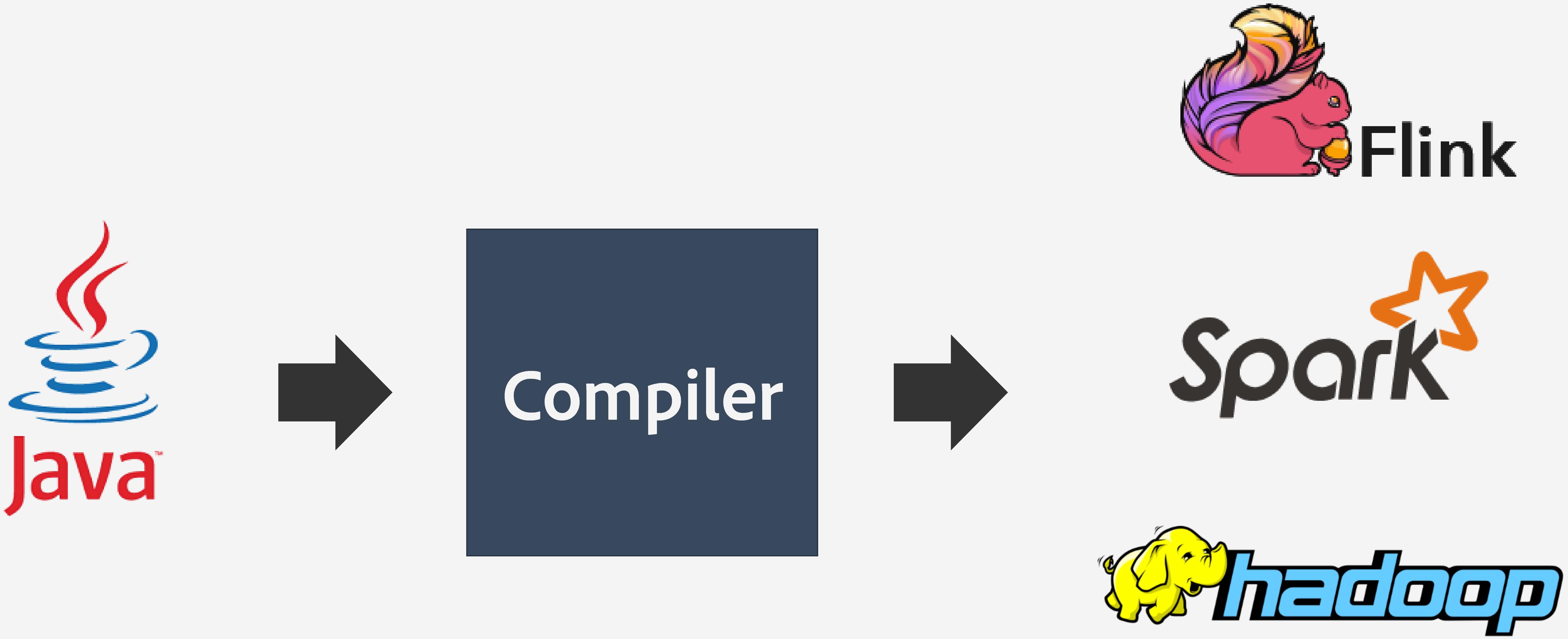
Java

Flink

Spark

hadoop

Option 2: Build a Compiler



Why is the sequential to MapReduce re-write difficult to automate?

Syntax Directed Translation

- Traditionally compilers use pattern-matching rules to do code transformations.

```
for (int i=0; i < $in.size(); ++i)
{
  if ($in.get(i) > $c)
    $out.add($in.get(i));
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$out.union($in.filter(e -> e > $c));
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  HashMap<String,Double> contrib = new HashMap<>();
  for (Map.Entry<String,Double> r : ranks.entrySet()) {
    List<String> urls = grouped_links.get(r.getKey());
    if(urls != null) {
      int size = urls.size();
      urls.forEach(dst -> {
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→ ??

A Synthesis Based Approach

Java

```java
int sum = 0;
for (Integer val : data) {
  sum += val * val;
}
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Re-write rules

Spark

```java
int sum = 0;
sum = data.map(val -> val*val)
          .reduce((v1,v2) -> v1+v2);
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A Synthesis Based Approach

$\lambda_{m(v)} \rightarrow v \ * v$

$\lambda_{r(v_1, v_2)} \rightarrow v_1 + v_2$

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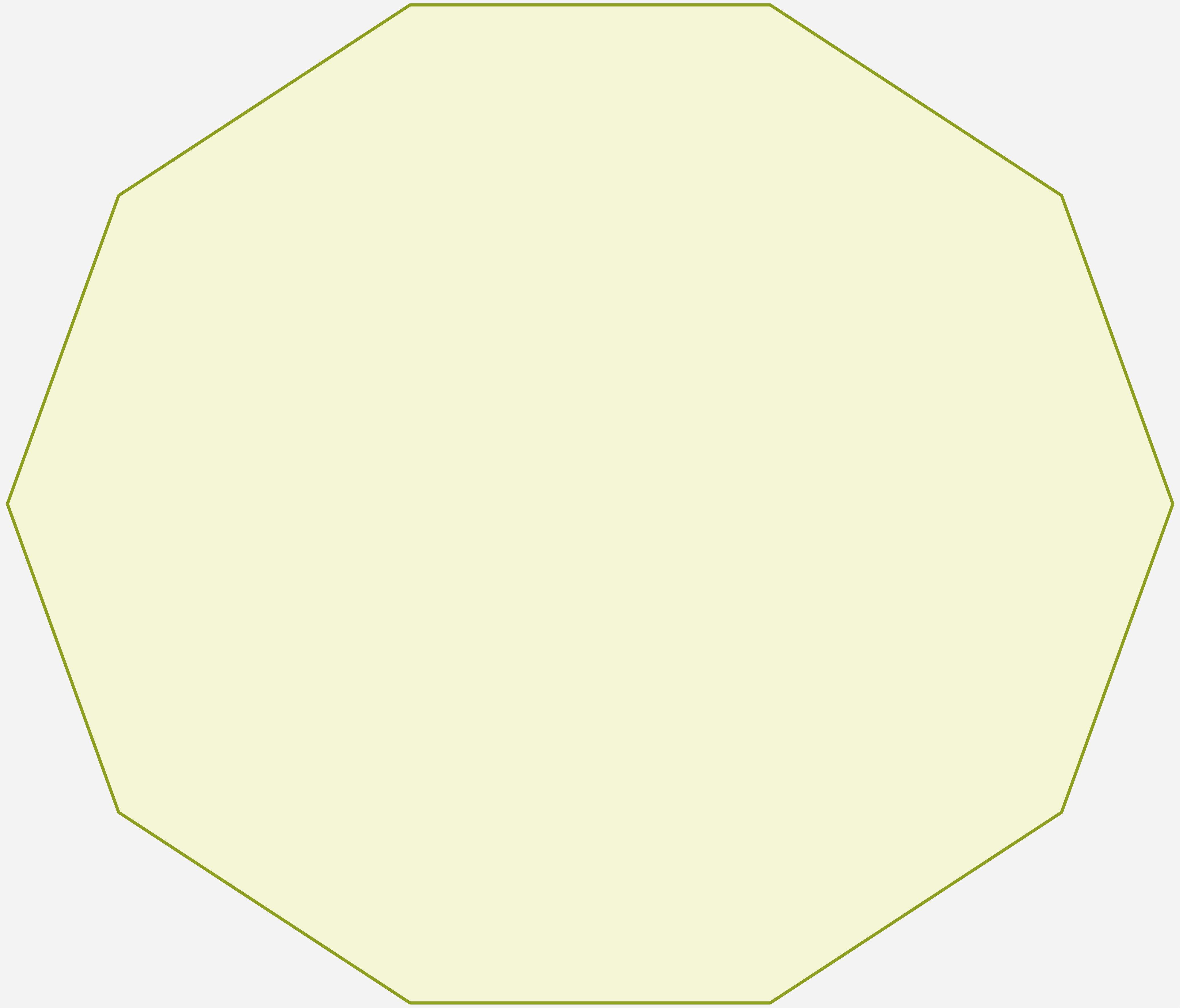
Space of programs constructed using ***map*** and ***reduce*** operators



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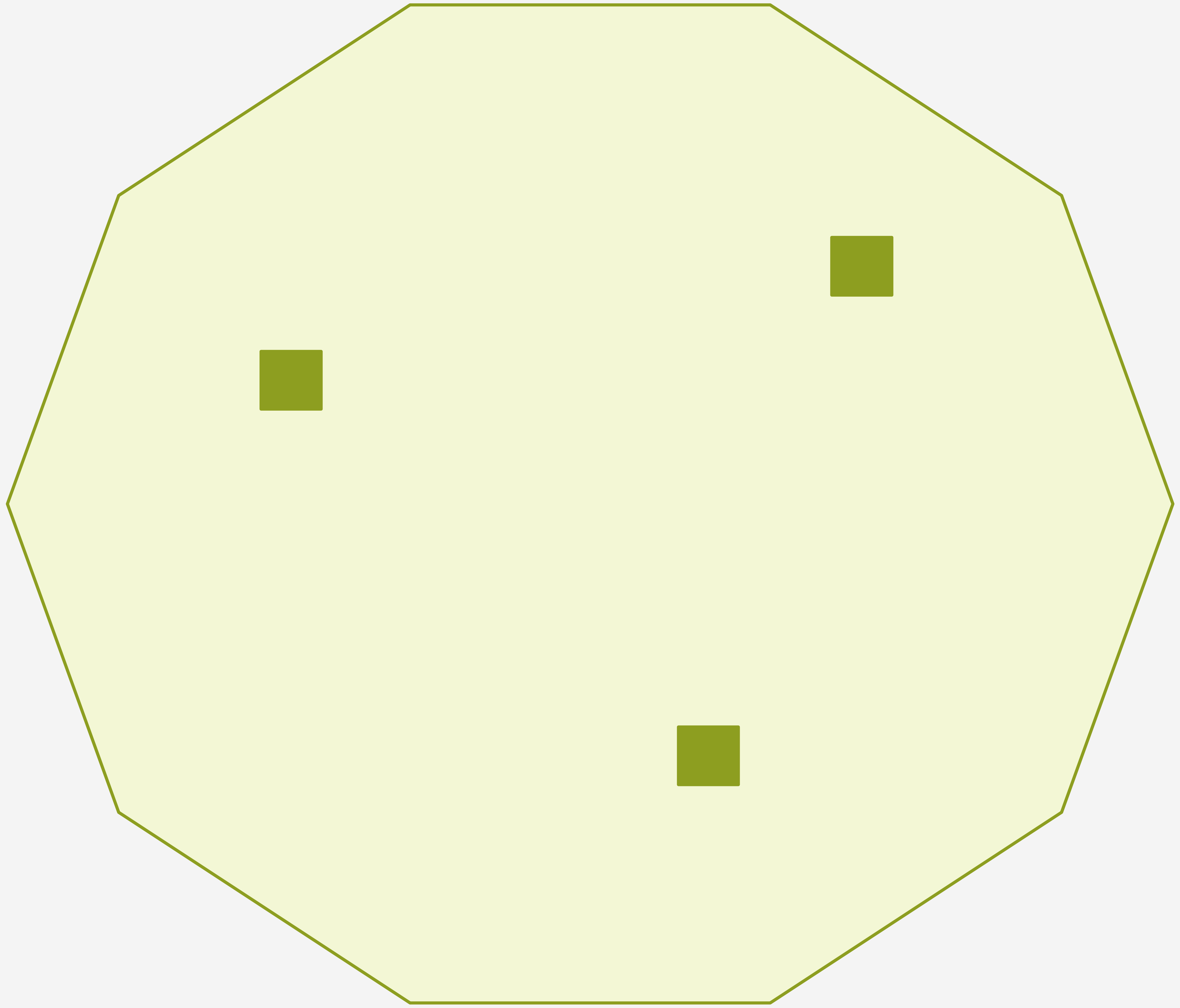

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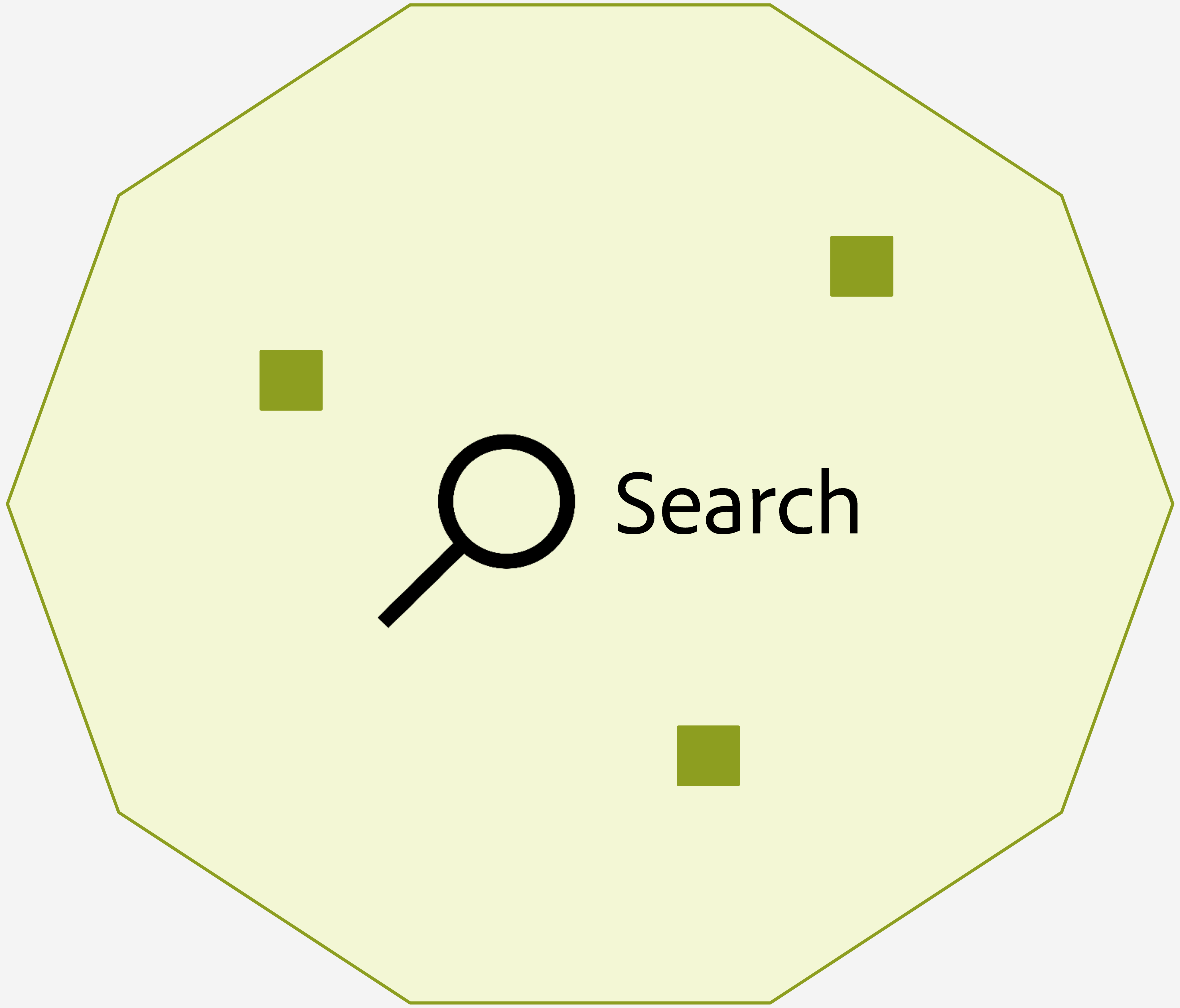

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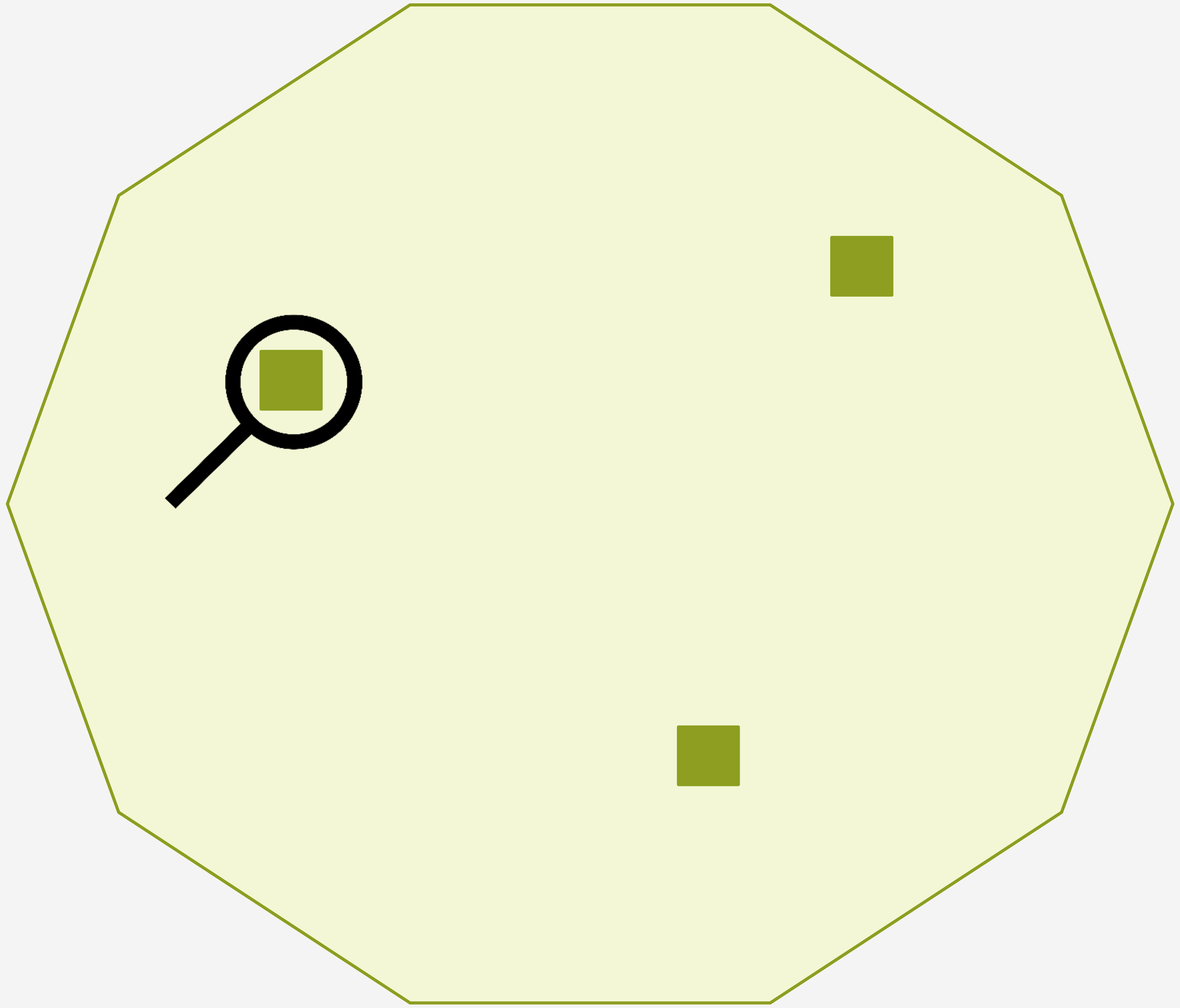
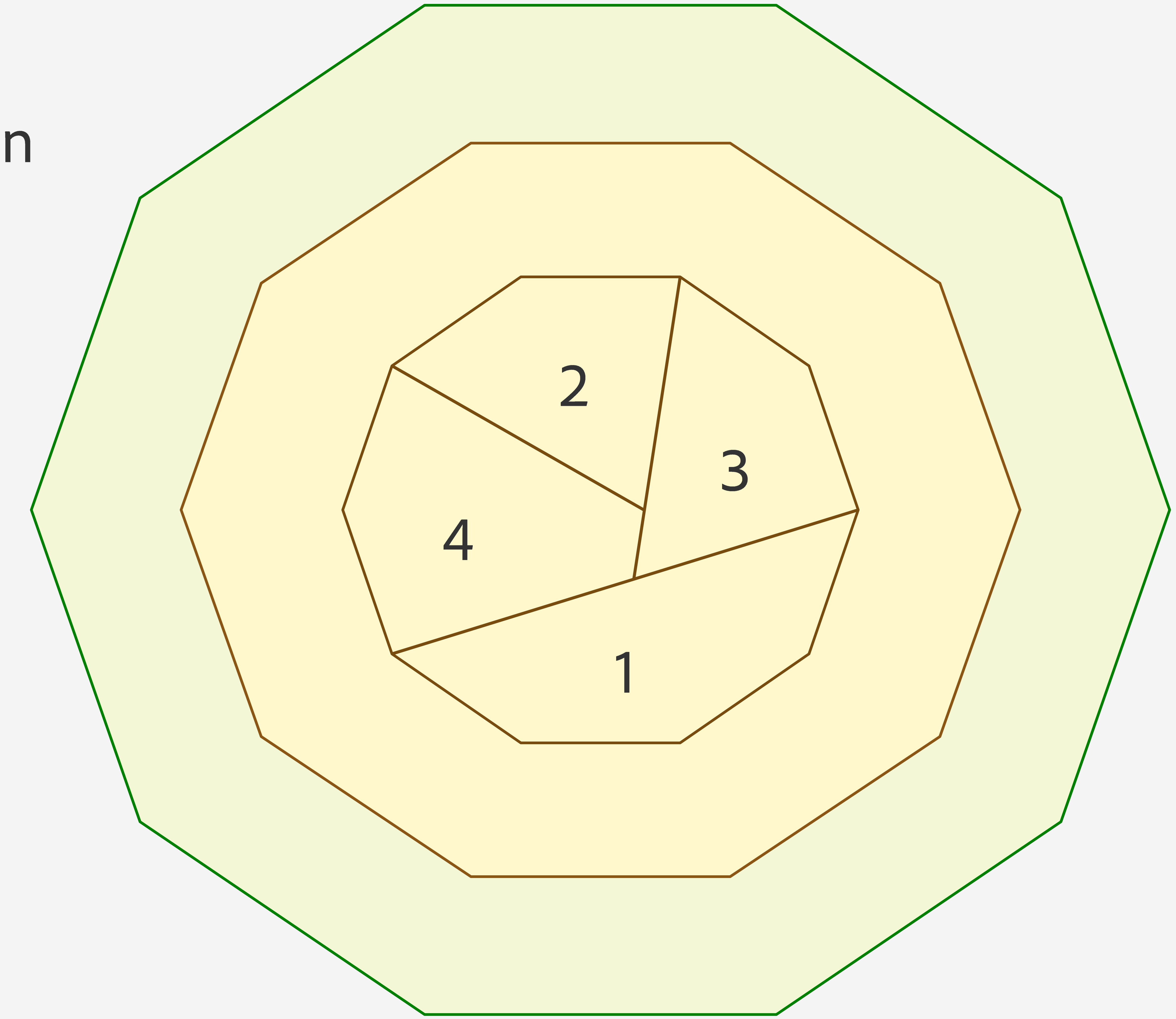


Making Search Manageable

- Design a concise API to express specification
- Use program analysis to specialize search
  - Ex: Only use specific operators
- Use incremental search
- Cost-based pruning



Introducing Casper

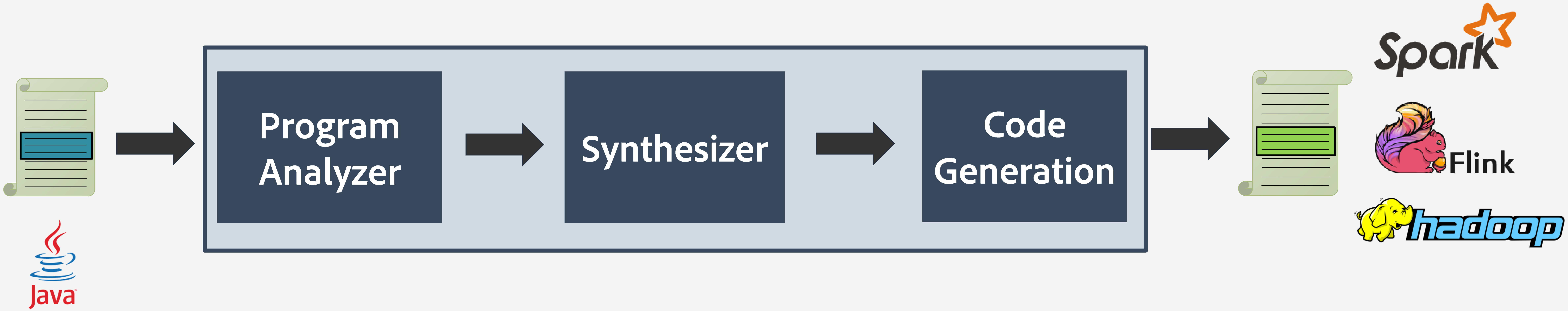
A compiler that automatically re-targets sequential Java applications to MapReduce frameworks.

Input

Un-annotated sequential Java application source code.

Output

An optimized version of the application that uses either Spark, Flink or Hadoop.



System Evaluation: Benchmarks

We used to optimize **55 benchmarks** collected from various sources.

Category	Description
Phoenix	Classical MapReduce problems
Fiji	Four open-sourced plugins implementing image processing algorithms
Bigλ	Big-Data analytics kernels
Ariths	Mathematical functions such as *sum*, *count*, *delta etc.*
Stats	Statistical functions such as *mean*, *variance*, *standard error* etc.
TPC-H	Java implementations for q1, q6, q15 and q17
Iterative	Page-rank and Logistic Regression based classification

Feasibility Analysis

Casper successfully translated **82** of the **101** identified code fragments across all benchmarks.

Causes of failures

- 3 caused by references to external library calls which were not currently supported
- 7 benchmarks could not be expressed in our intermediate language
- 9 benchmarks timed out (required more than 90 minutes)

Performance Analysis (Spark)

75GB data on a **10 node cluster** (8 cores, 30gb ram)

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Mean compilation time for one benchmark was **11.4 minutes.**

Median compilation time for one benchmark was **2.1 minutes.**

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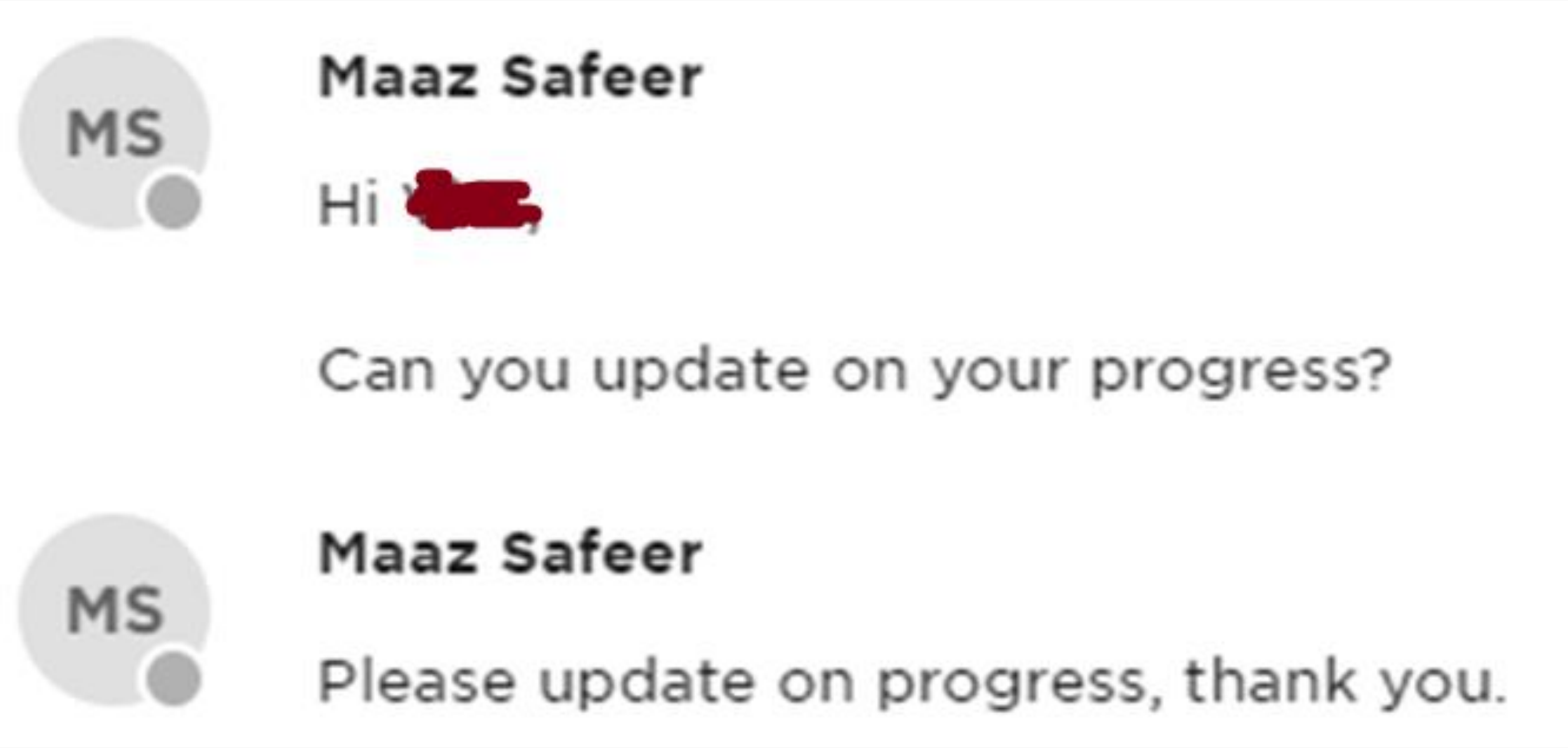
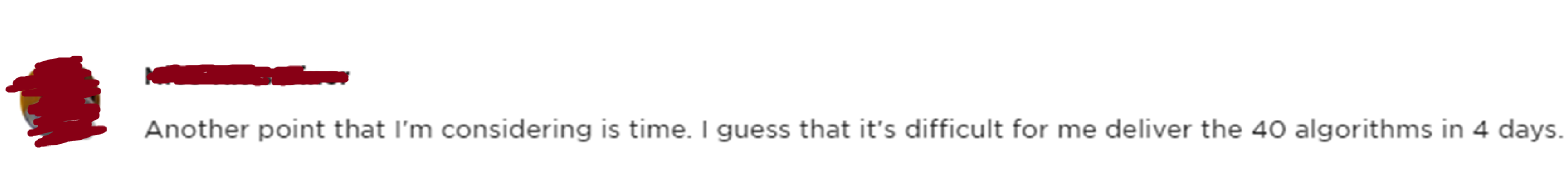
No managerial overhead!





Take-aways

- Casper can automatically translate a wide array of sequential applications to MapReduce.

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casper.uwplse.org

Paper | Online Demo | Source Code