MLbase

www.mlbase.org

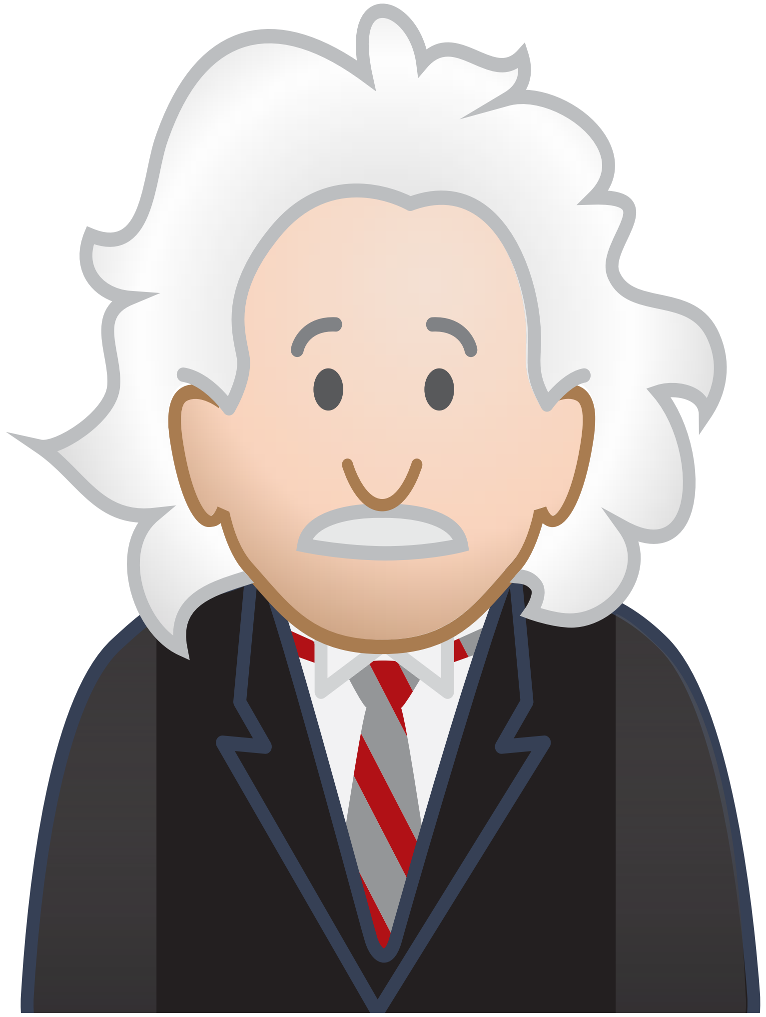
Evan Sparks and Ameet Talwalkar
UC Berkeley

Collaborators: Tim Kraska[2], Virginia Smith[1], Xinghao Pan[1], Shivaram Venkataraman[1], Matei Zaharia[1], Rean Griffith[3], John Duchi[1], Joseph Gonzalez[1], Michael Franklin[1], Michael I. Jordan[1]

[1]UC Berkeley [2]Brown [3]VMware

amplab UC Berkeley

Problem: Scalable implementations *difficult* for ML Developers…



Problem: Scalable implementations *difficult* for ML Developers…

MATLAB
The Language of Technical Computing

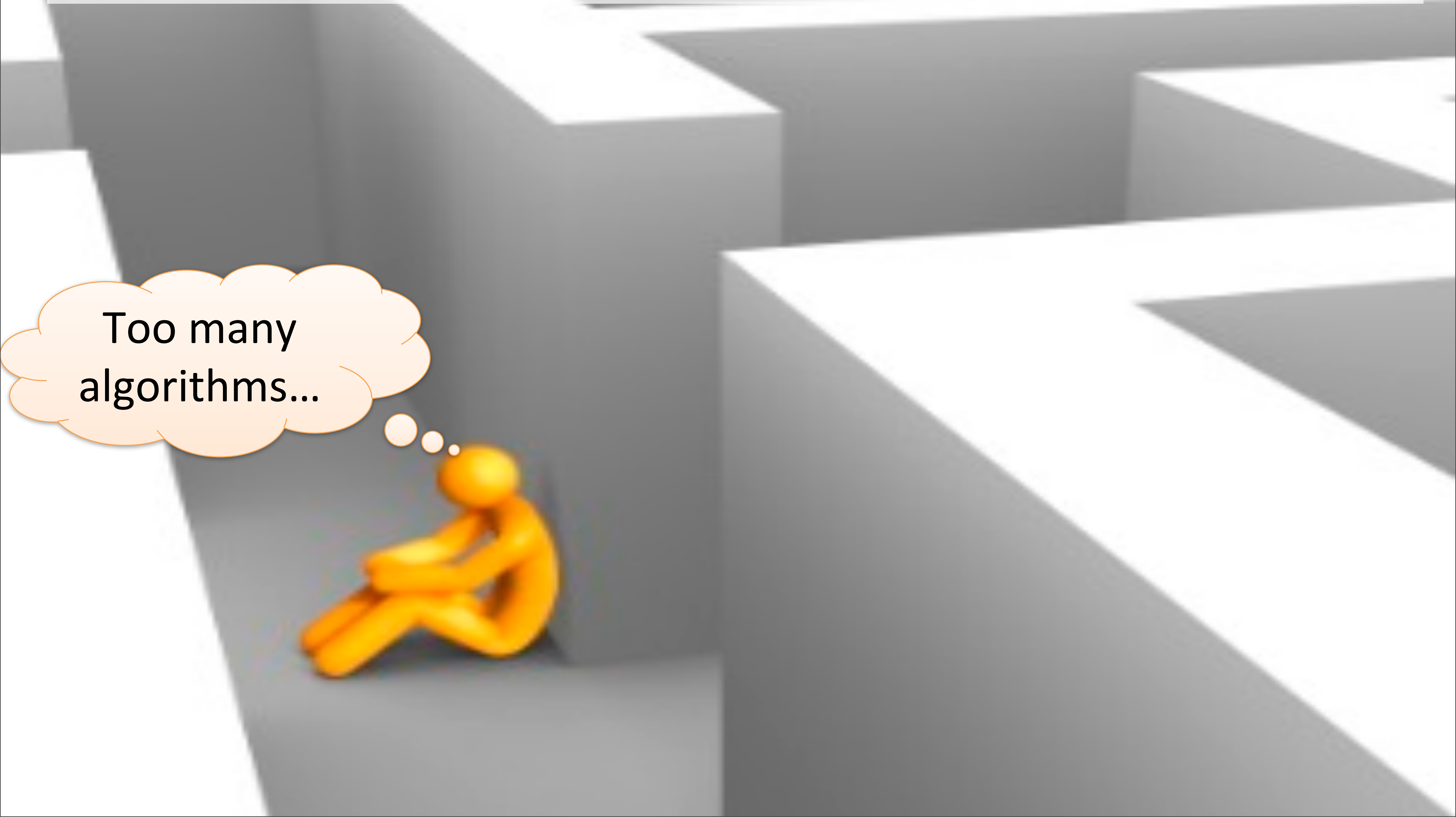
Problem: Scalable implementations *difficult* for ML Developers…

VOWPAL WABBIT

mahout

GraphLab

Problem: ML is *difficult* for End Users…



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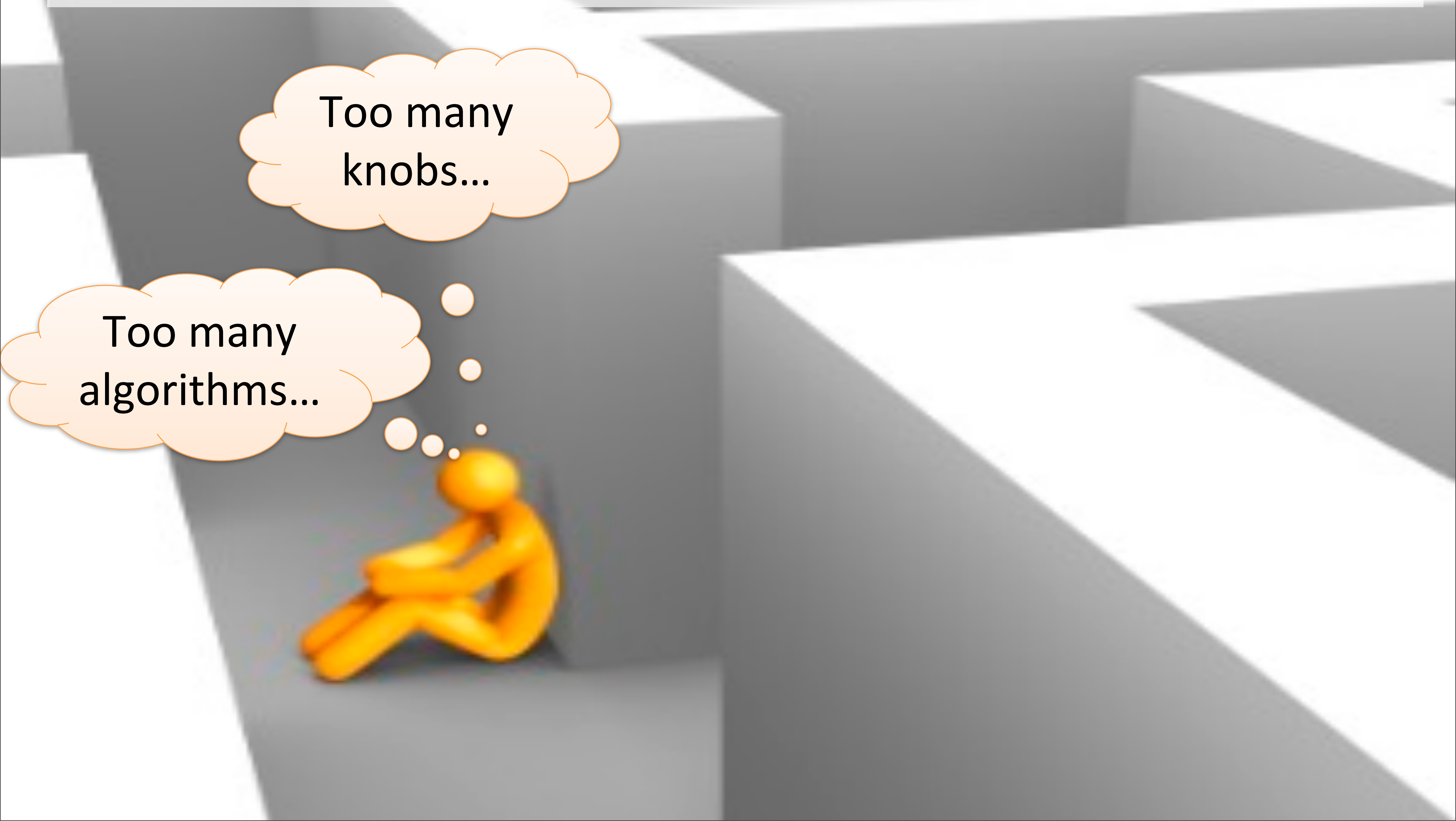

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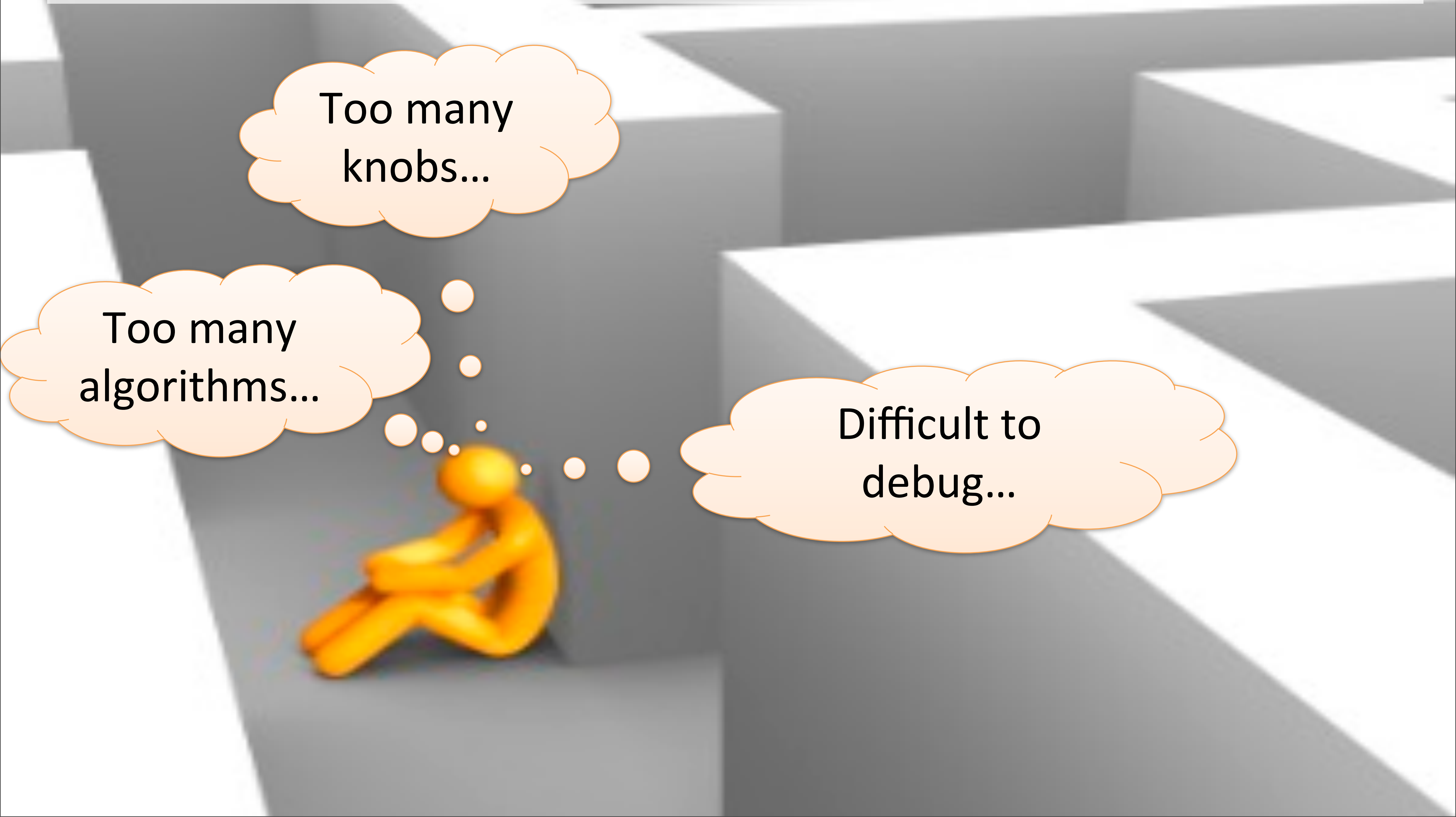

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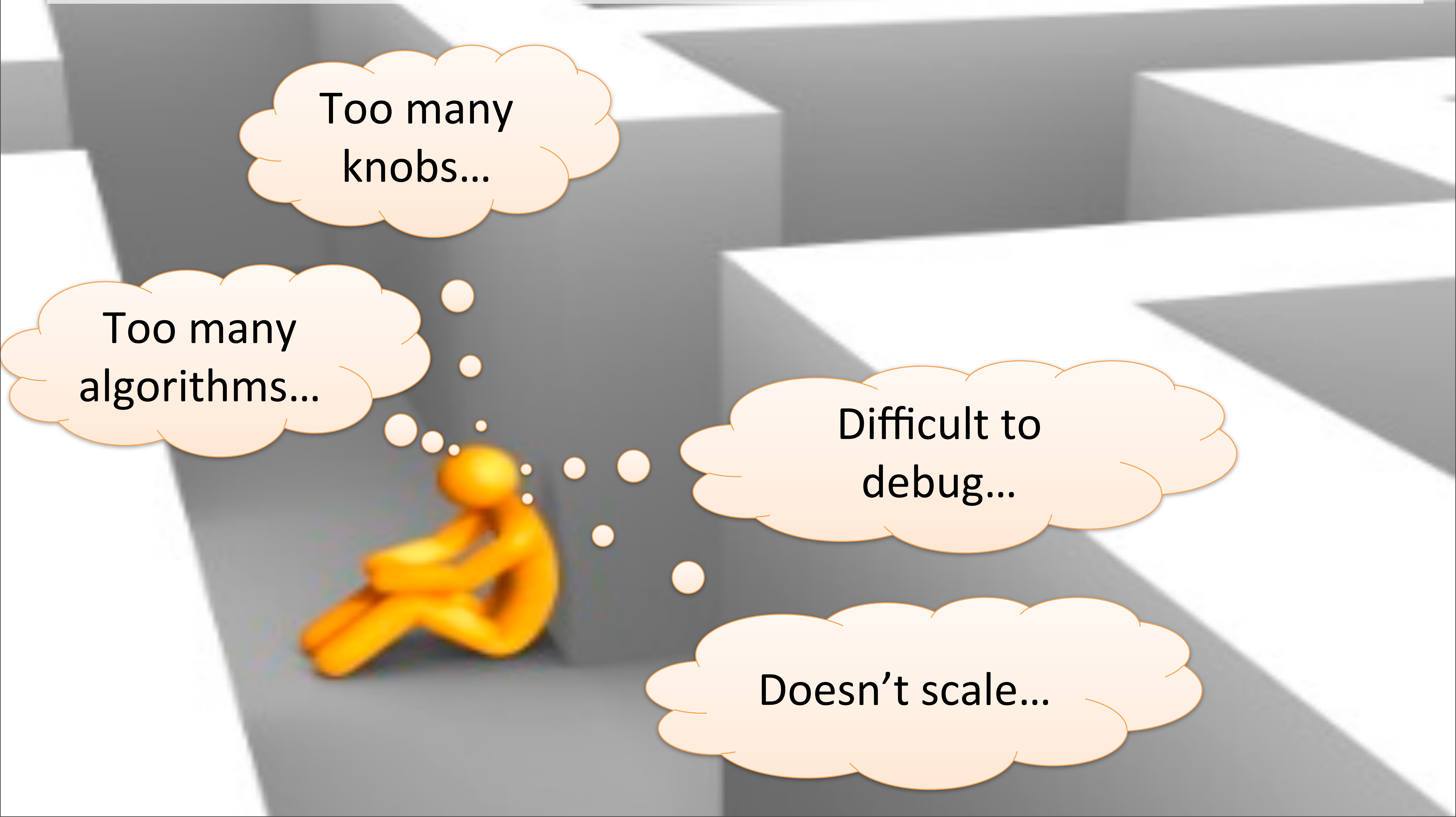

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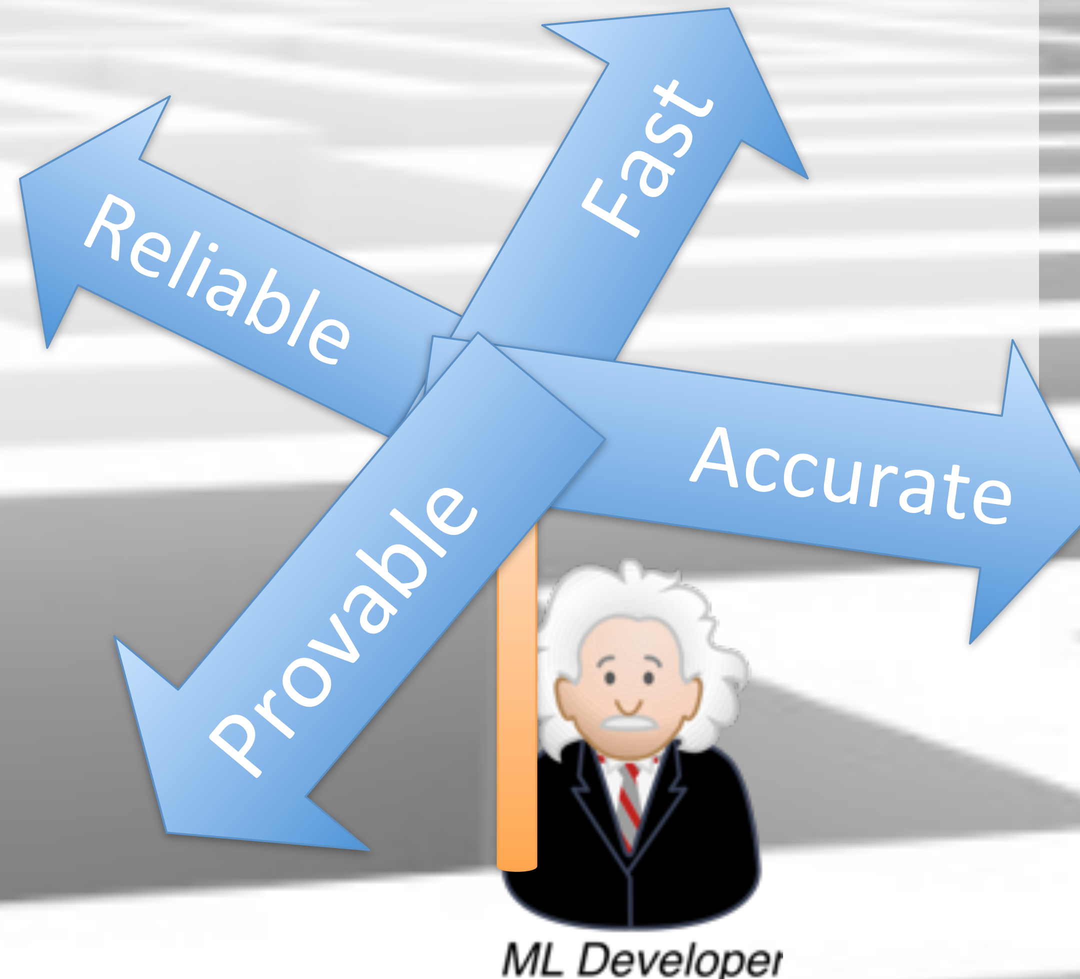


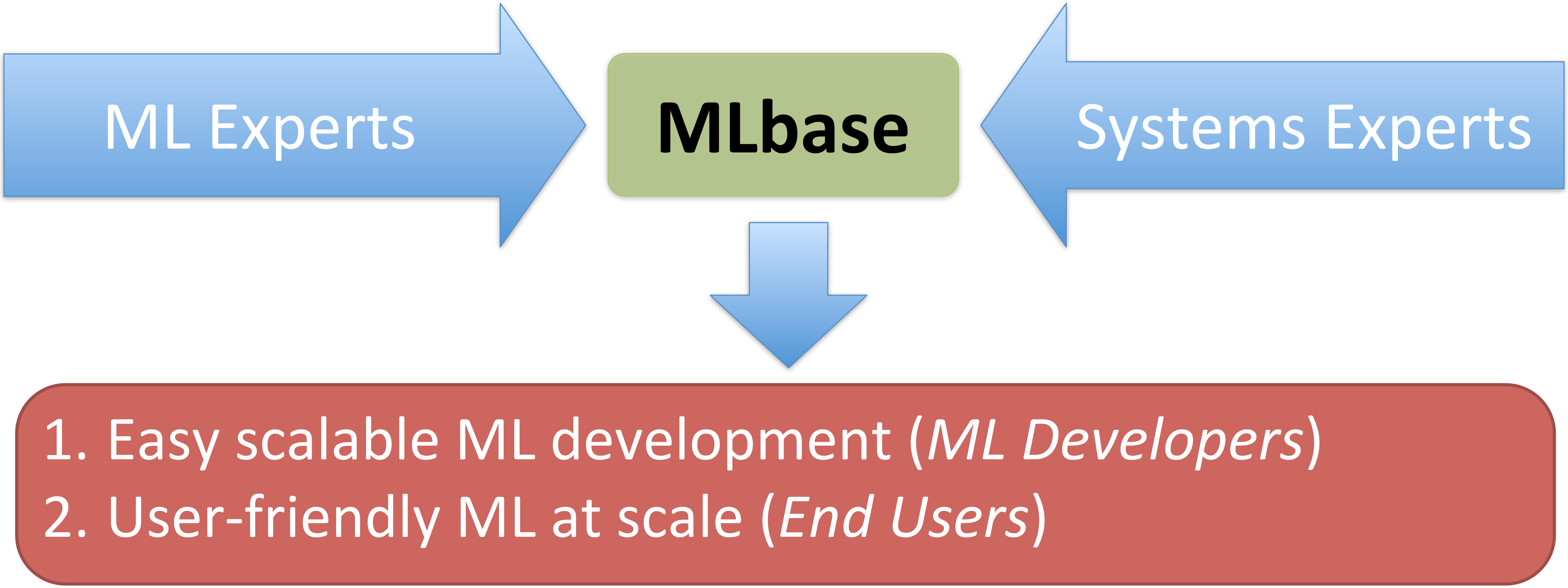
Too many knobs…

Too many algorithms…

Difficult to debug…

Doesn't scale…


ML Experts
MLbase
Systems Experts


ML Experts
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1. Easy scalable ML development (*ML Developers*)
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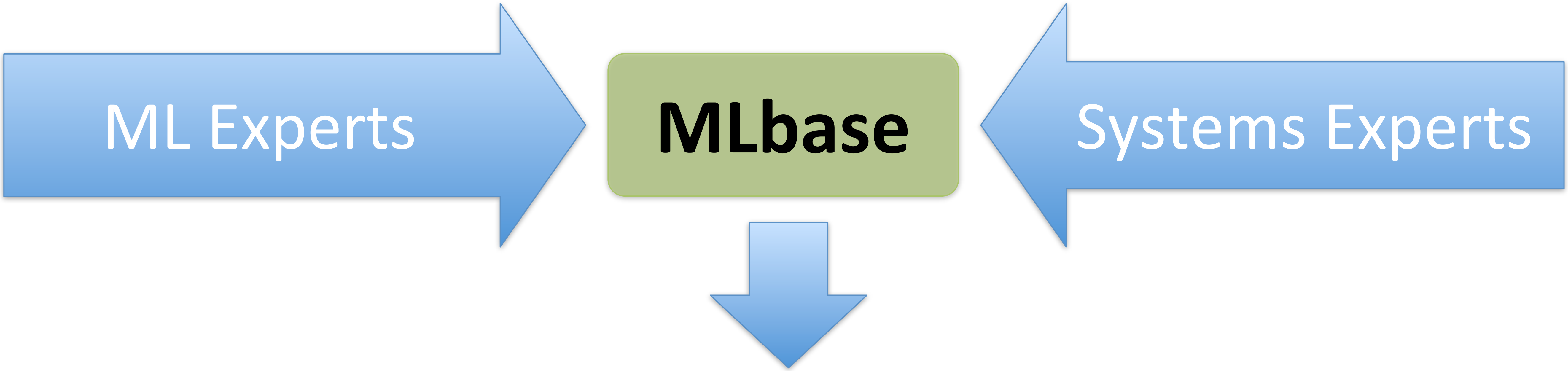


1. Easy scalable ML development (*ML Developers*)
2. User-friendly ML at scale (*End Users*)

Along the way, we gain insight into data intensive computing

Vision

MLI Details

Current Status

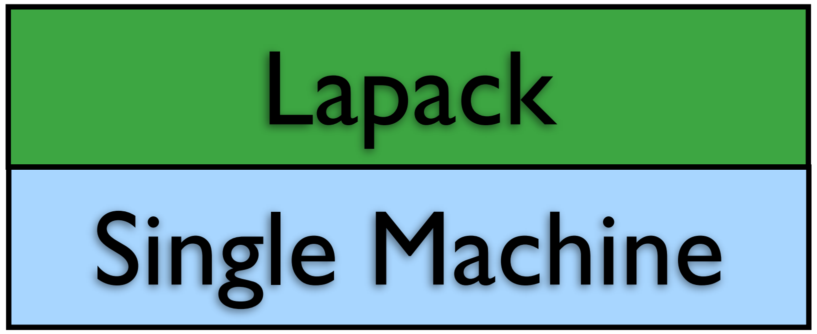
ML Workflow

Matlab Stack

Matlab Stack

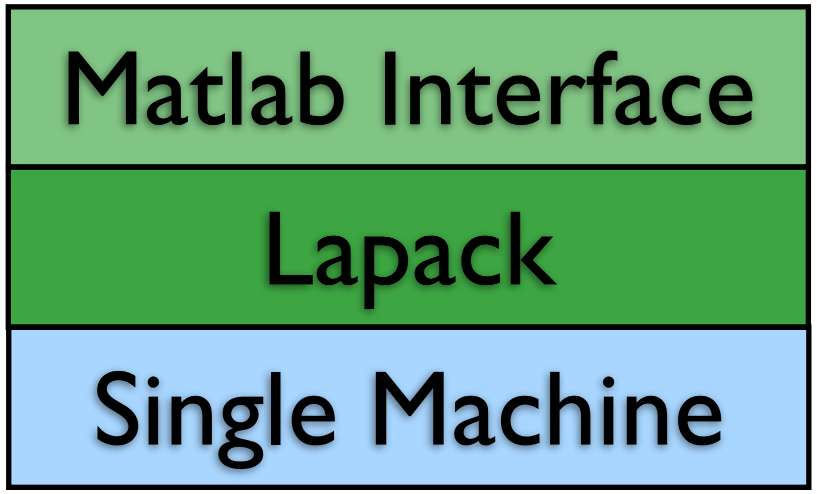
Single Machine

Matlab Stack



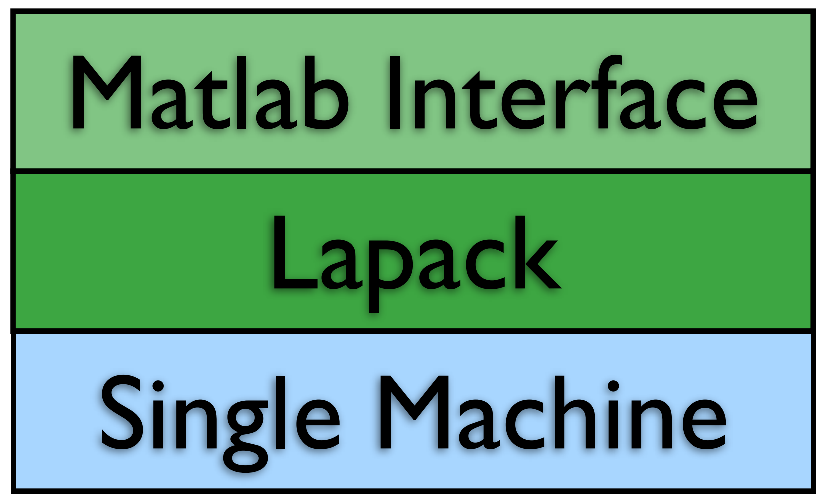
- Lapack: low-level Fortran linear algebra library

Matlab Stack



- Lapack: low-level Fortran linear algebra library
- Matlab Interface
  - Higher-level abstractions for data access / processing
  - More extensive functionality than Lapack
  - Leverages Lapack whenever possible

Matlab Stack



- Lapack: low-level Fortran linear algebra library
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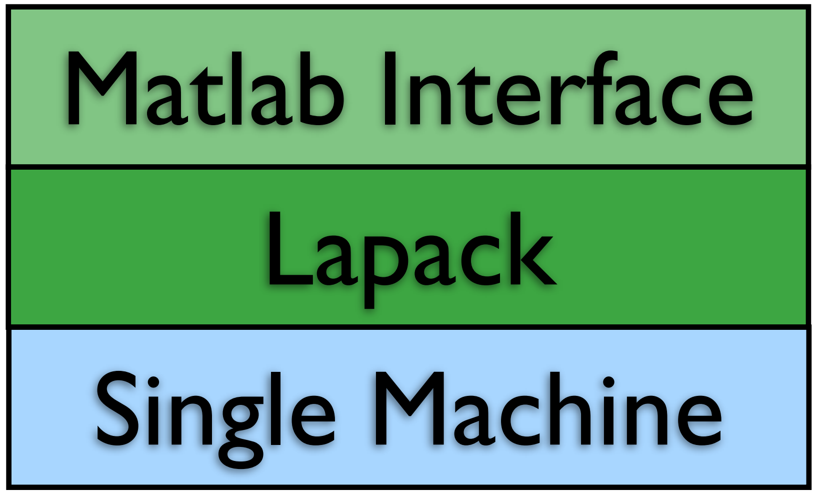
  - Higher-level abstractions for data access / processing
  - More extensive functionality than Lapack
  - Leverages Lapack whenever possible
- Similar stories for R and Python

MLbase Stack



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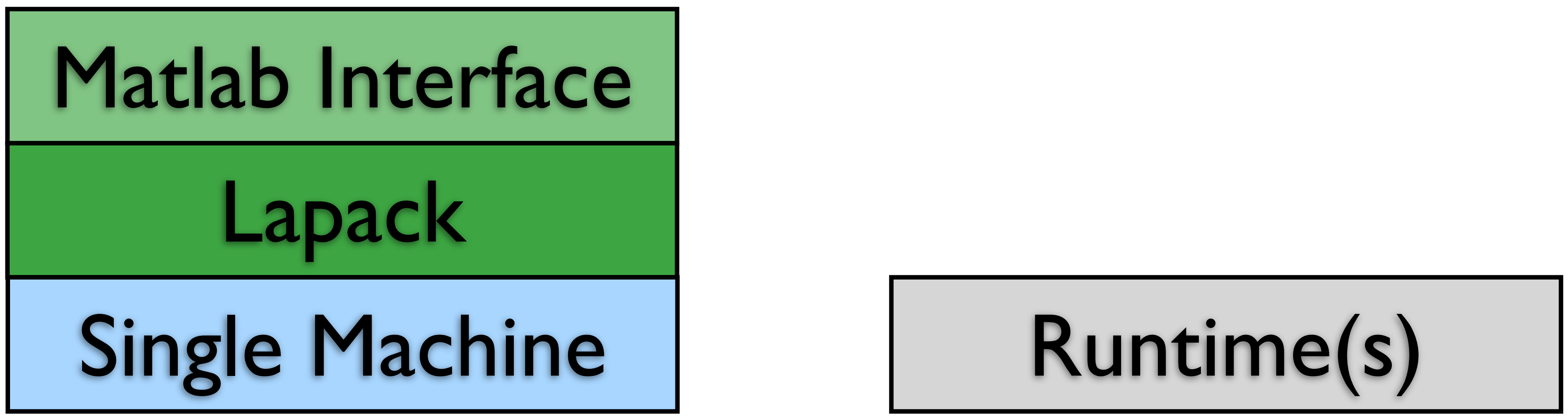

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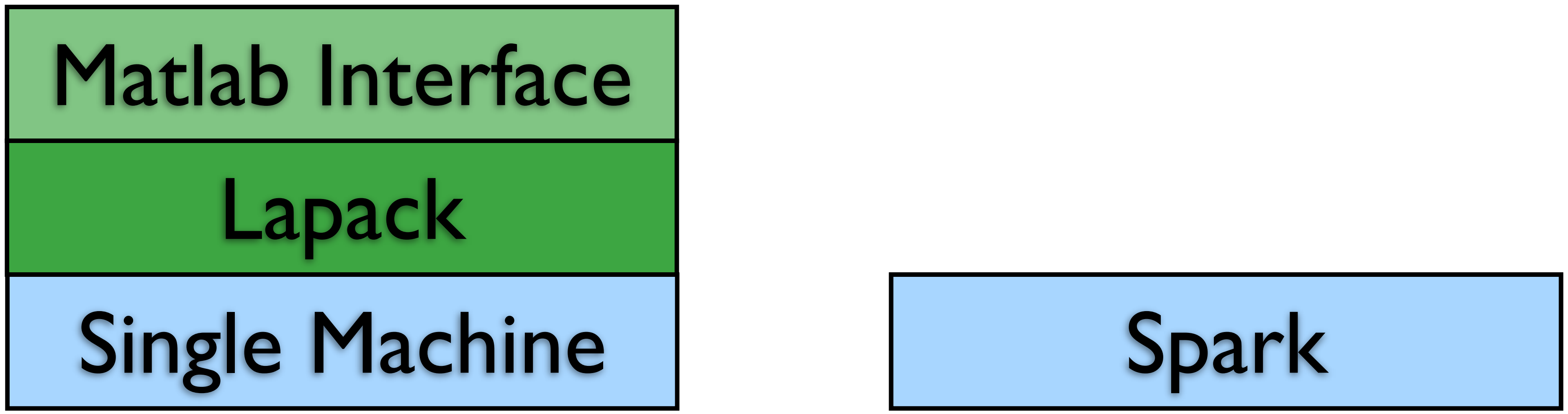
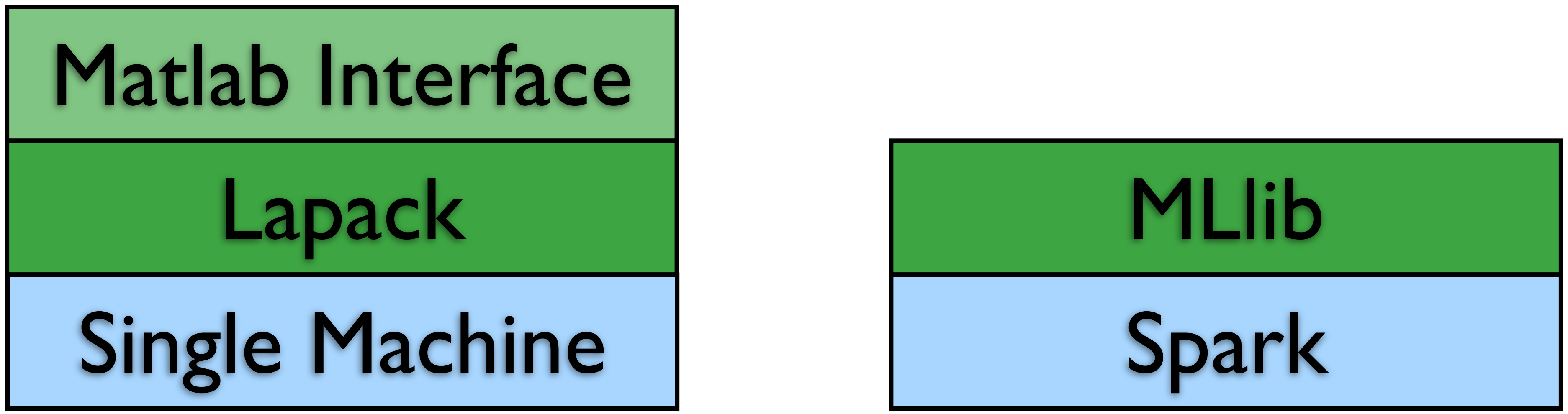


Spark: cluster computing system designed for iterative computation

MLbase Stack



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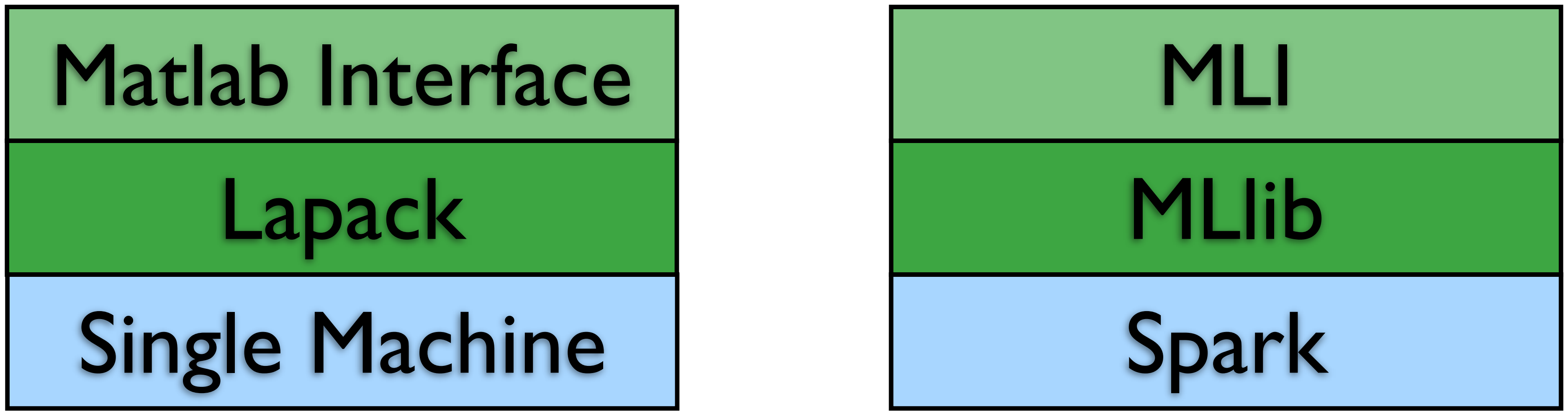
MLbase Stack



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MLI: API / platform for feature extraction and algorithm development

- Platform independent

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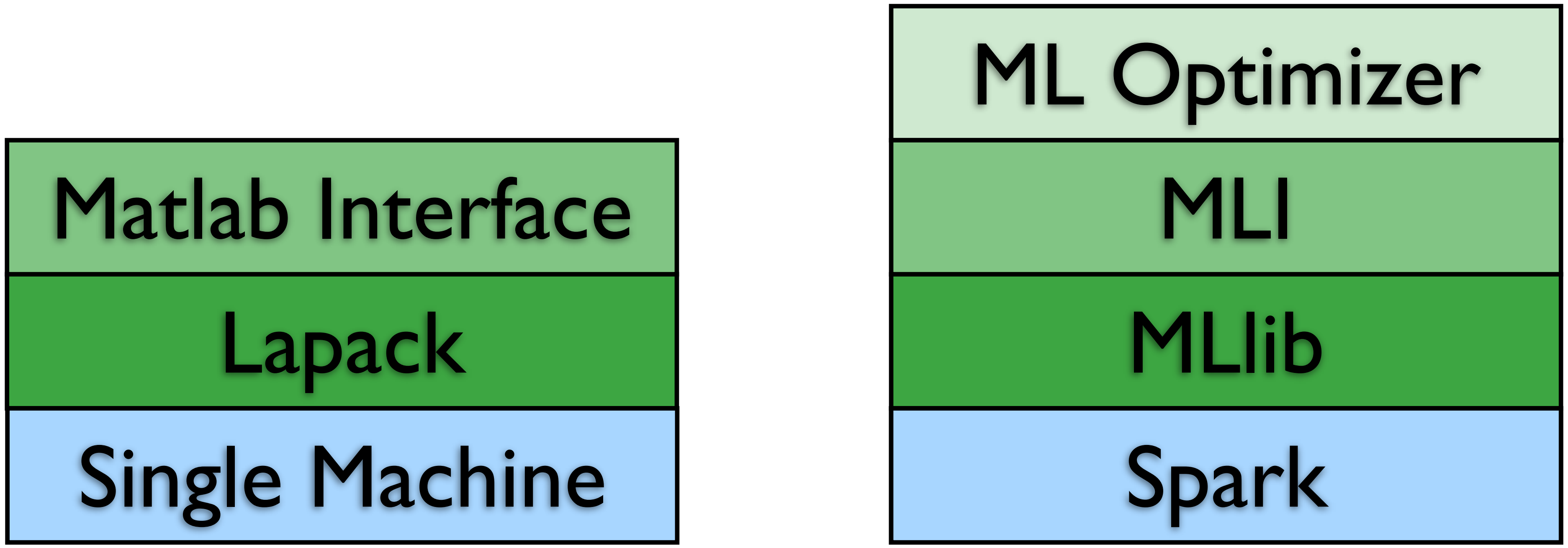

Spark: cluster computing system designed for iterative computation

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MLI: API / platform for feature extraction and algorithm development

- Platform independent

ML Optimizer: automates model selection

- Solves a search problem over feature extractors and algorithms in MLI

Example: MLlib

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- Goal: Classification of text file

Example: MLlib

```scala
def main(args: Array[String]) {
  val sc = new SparkContext("local", "SparkLR")

  //Load data from HDFS
  val data = sc.textFile(args(0))  //RDD[String]

  //User is responsible for formatting/featurizing/normalizing their RDD!
  val featurizedData: RDD[(Double,Array[Double])] = processData(data)
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  //Train the model using MLlib.
  val model = new LogisticRegressionLocalRandomSGD()
                  .setStepSize(0.1)
                  .setNumIterations(50)
                  .train(featurizedData)
}
```

- Goal: Classification of text file
- Featurize data manually
- Calls MLlib's LR function

Example: MLI

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```
def main(args: Array[String]) {
        val mc = new MLContext("local", "MLILR")

        //Read in file from HDFS
        val rawTextTable = mc.csvFile(args(0), Seq("class","text"))

        //Run feature extraction
        val classes = rawTextTable(??, "class")
        val ngrams = tfIdf(nGrams(rawTextTable(??, "text"), n=2, top=30000))
        val featureizedTable = classes.zip(ngrams)
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- Use built-in feature extraction functionality

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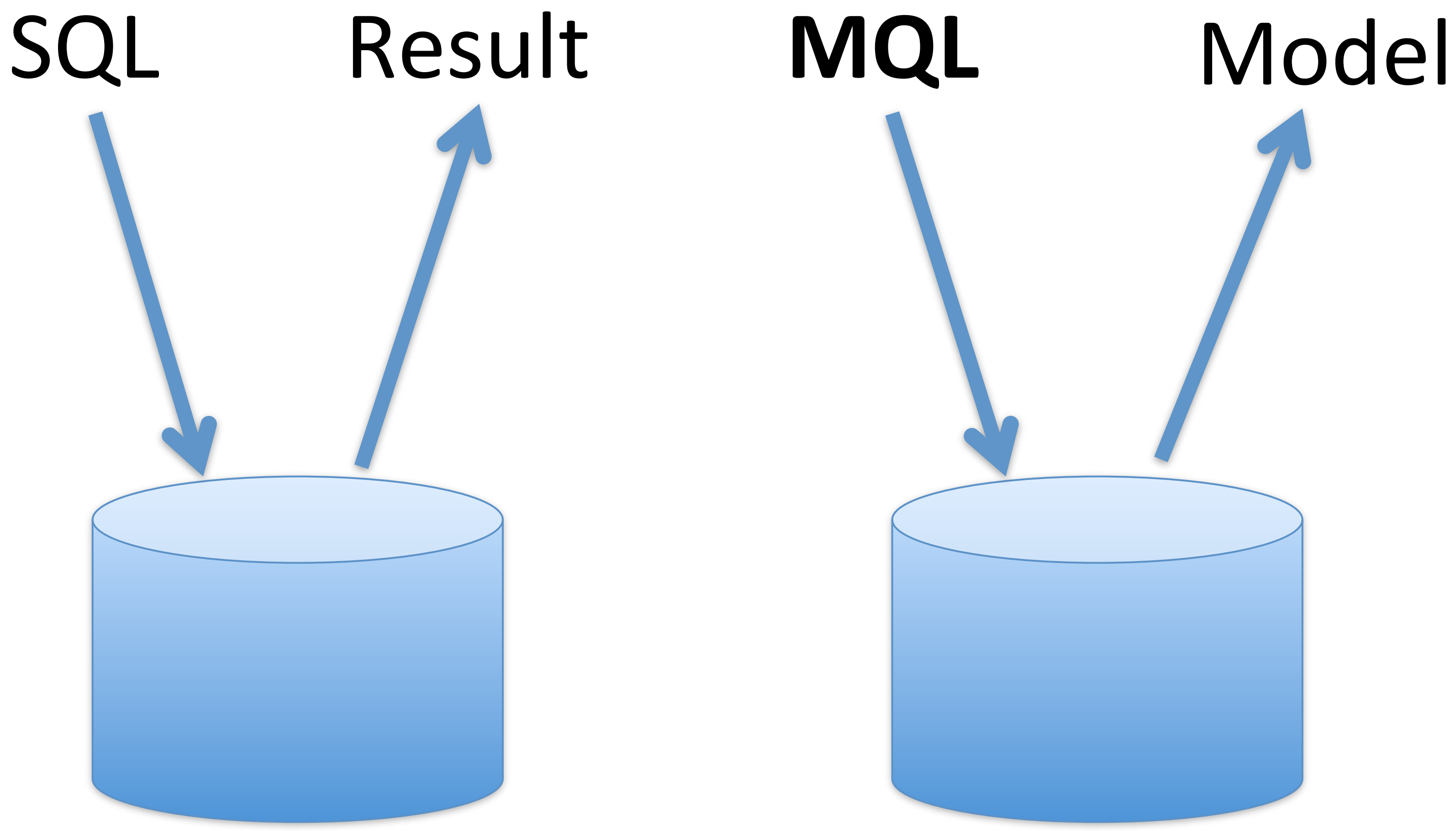
- Use built-in feature extraction functionality
- MLI Logistic Regression leverages MLlib
- Extensions:
  - Embed in cross-validation routine
  - Use different feature extractors / algorithms
  - Write new ones

Example: ML Optimizer

```
var X = load("text_file", 2 to 10)
var y = load("text_file", 1)
var (fn-model, summary) = doClassify(X, y)
```

- User declaratively specifies task
- ML Optimizer searches through MLI

Example: ML Optimizer



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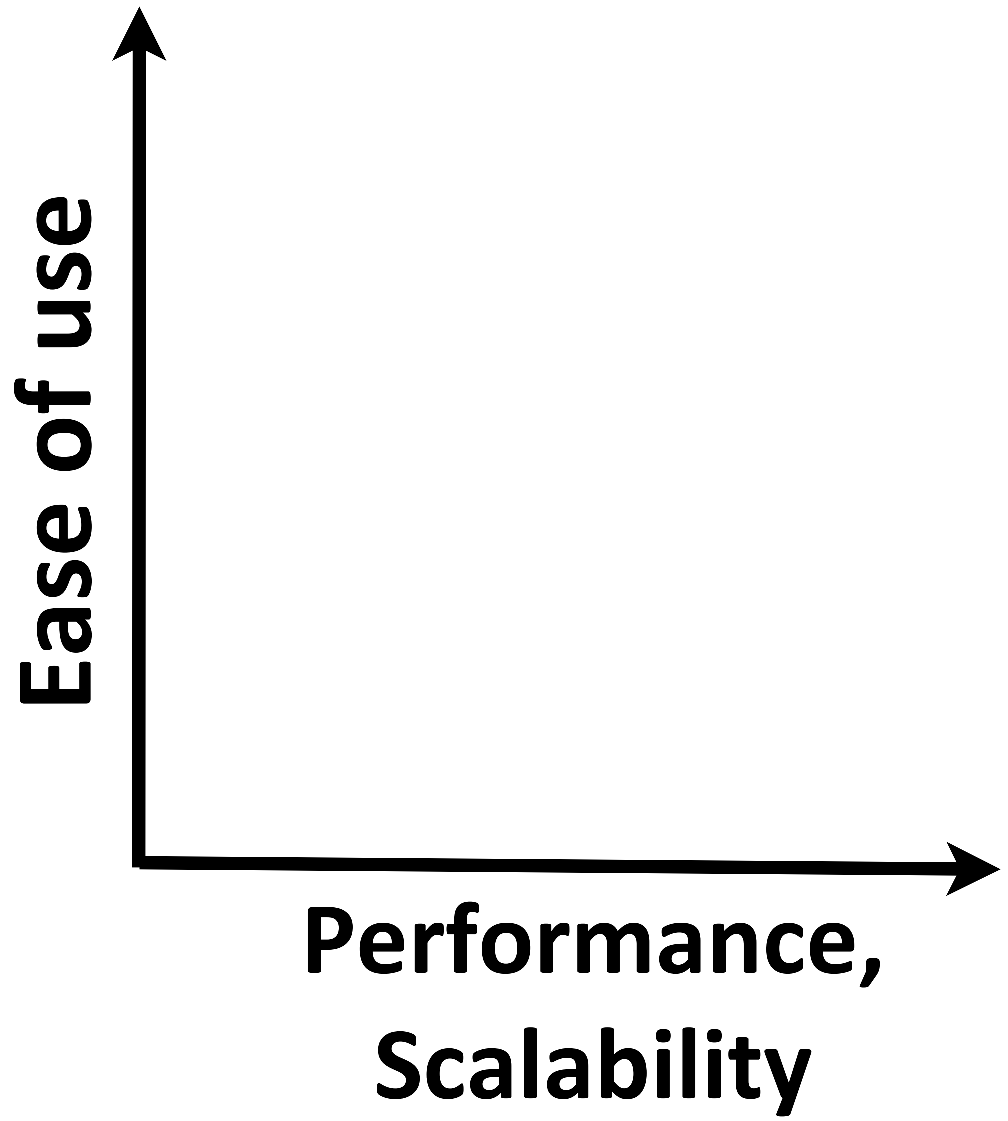

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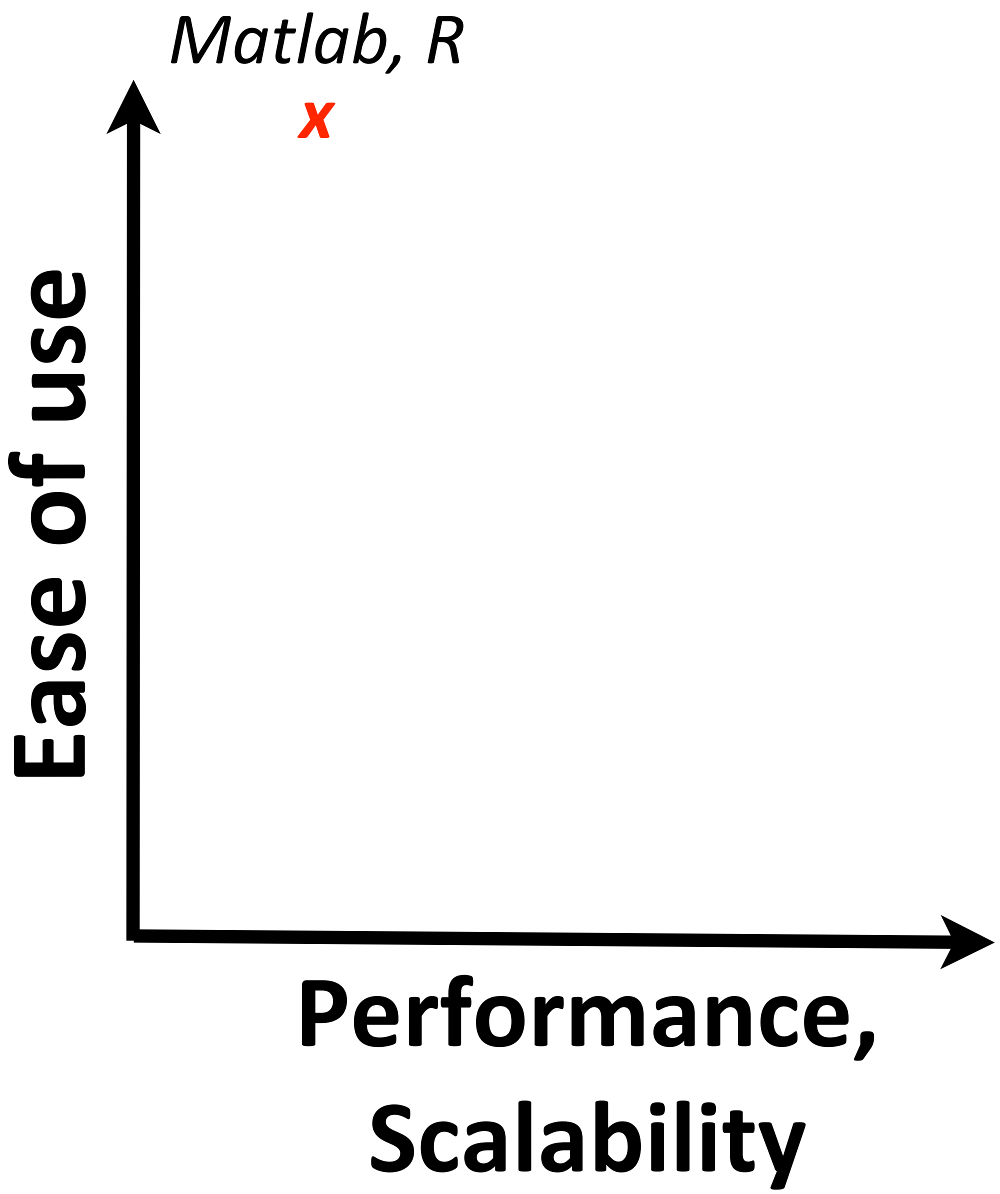

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- \+ Sufficient for prototyping / writing papers
- — Ad-hoc, non-scalable scripts
- — Loss of translation upon re-implementation

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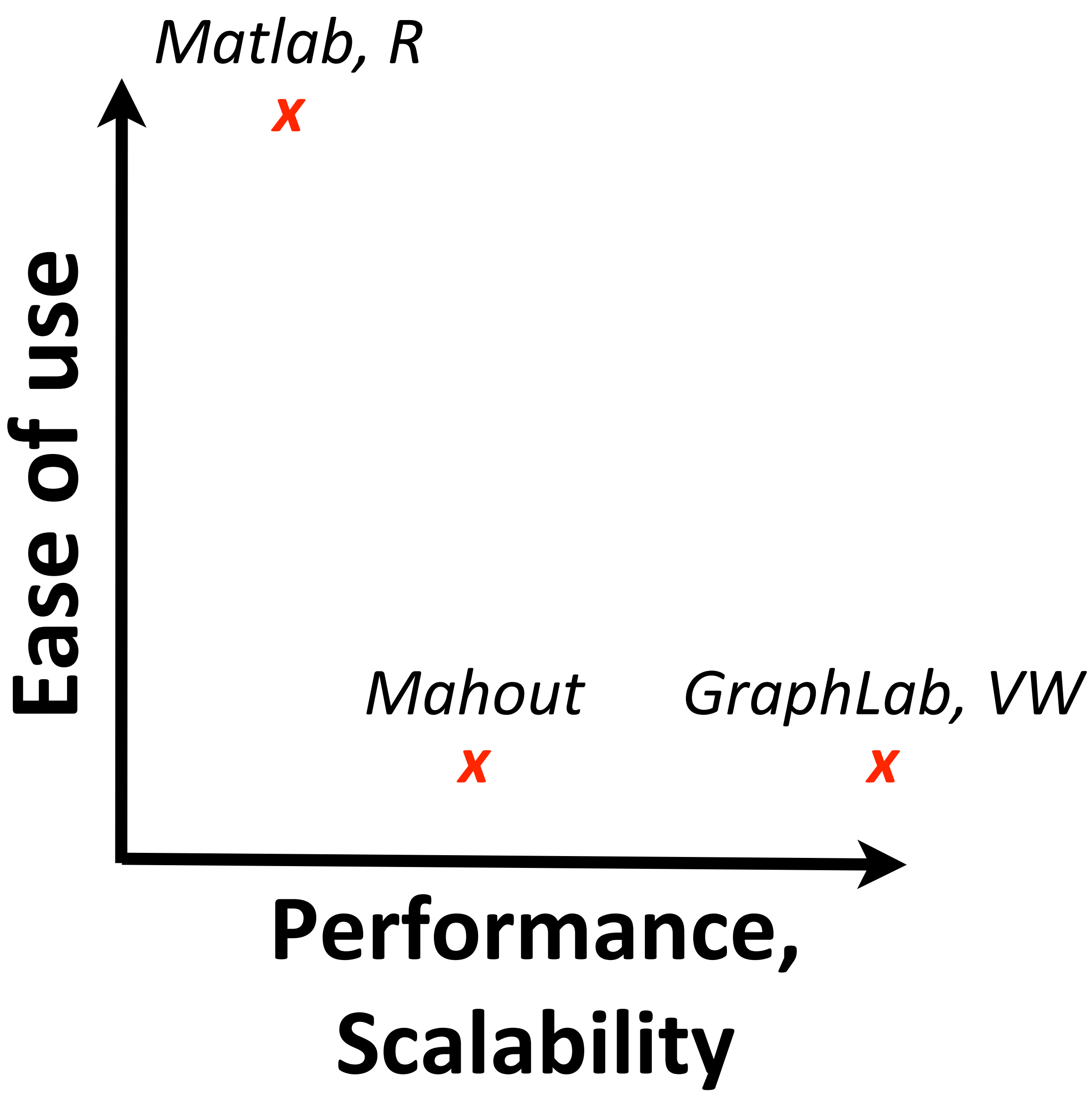

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+ Existing open-source libraries
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- Initial studies in MATLAB (Not distributed)
- Distributed prototype involving compiled MATLAB

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- Theory: simple if-statement (3 lines of code)
- Practice: sift through 7 files, nearly 1K lines of code

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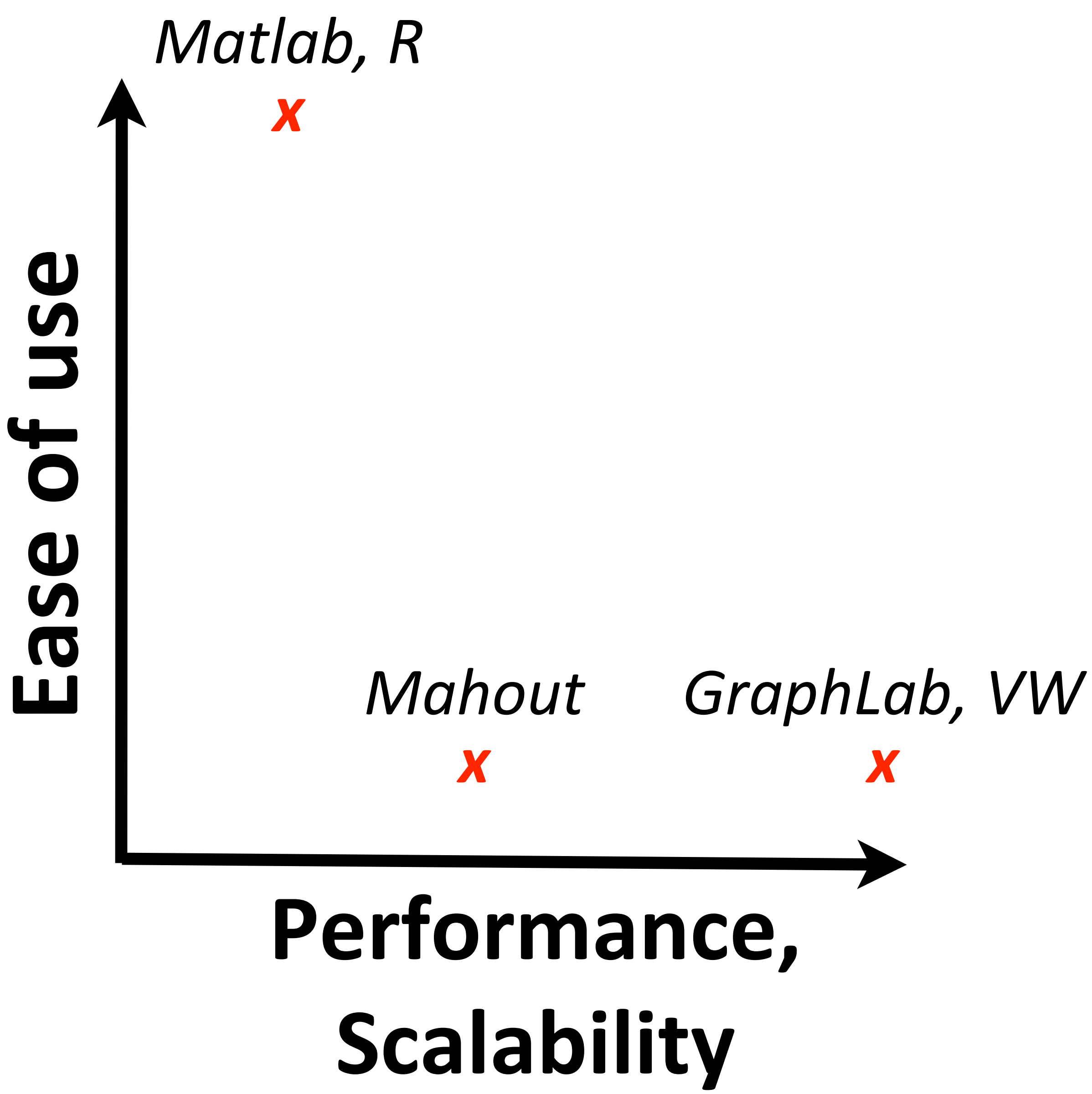

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R

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mahout

VOWPAL WABBIT GraphLab

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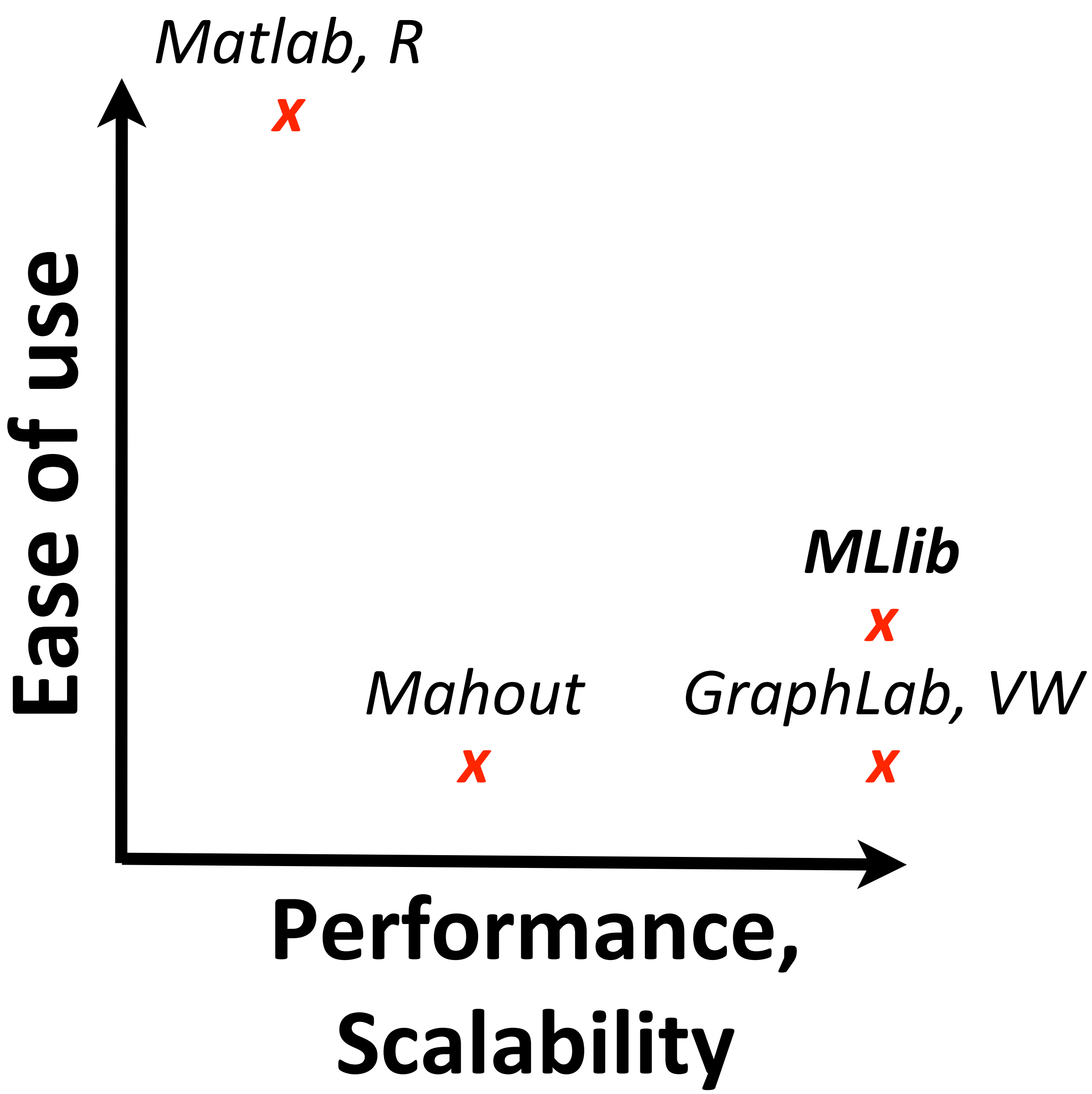

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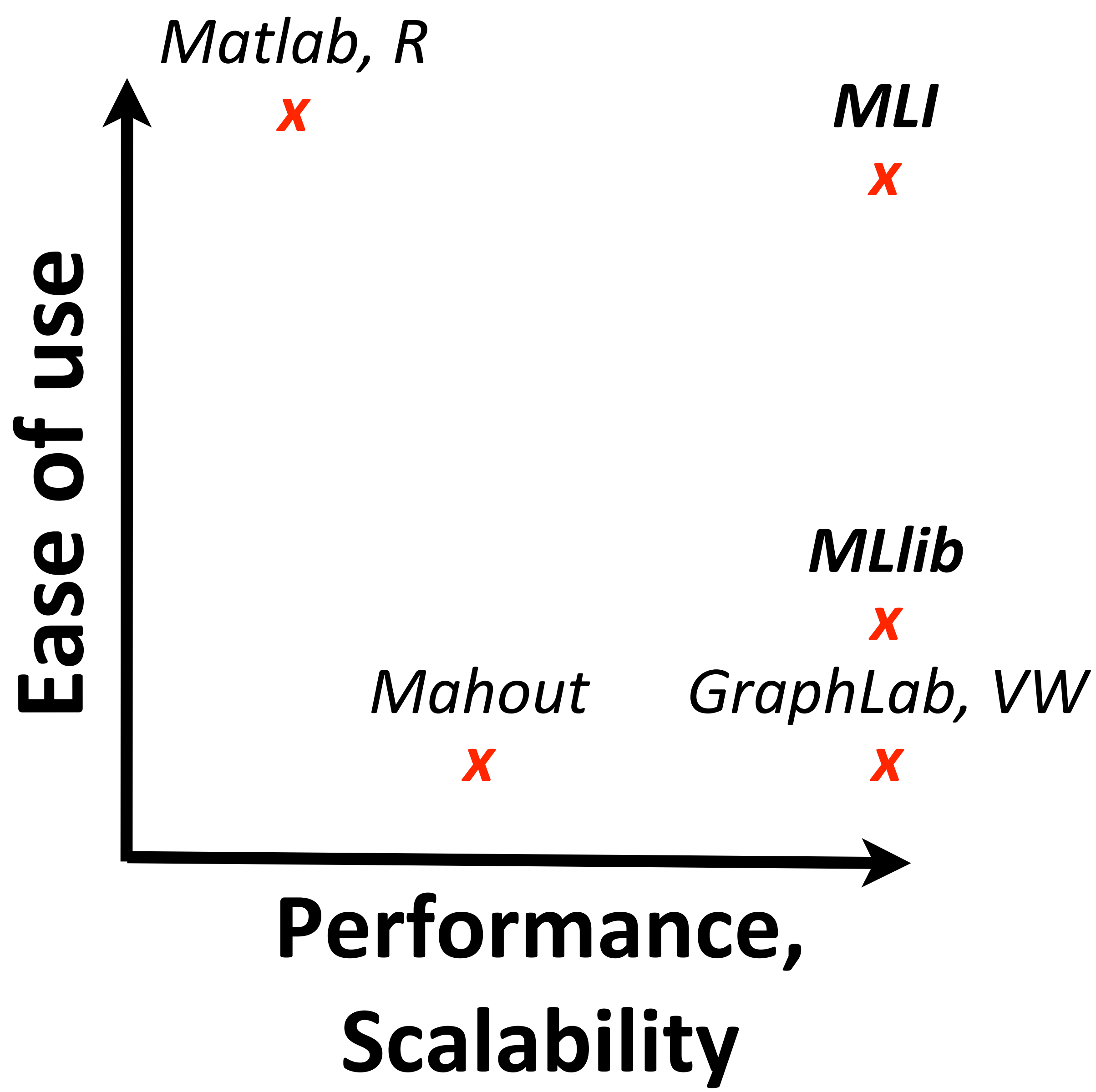

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NEW

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NEW

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- Abstract interface for arbitrary backend
- Common interface to support an optimizer

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- DFC: ~50 lines of code
- ALS: early stopping in 3 lines; < 40 lines total

MLI Ease of Use

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Logistic Regression

System	Lines of Code
Matlab	11

Alternating Least Squares

System	Lines of Code
Matlab	20

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GraphLab	383

MLI Ease of Use

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MLI	32

MLI/Spark Performance

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- **EC2 Experiments**
  - m2.4xlarge instances, up to 32 machine clusters

Logistic Regression - Weak Scaling

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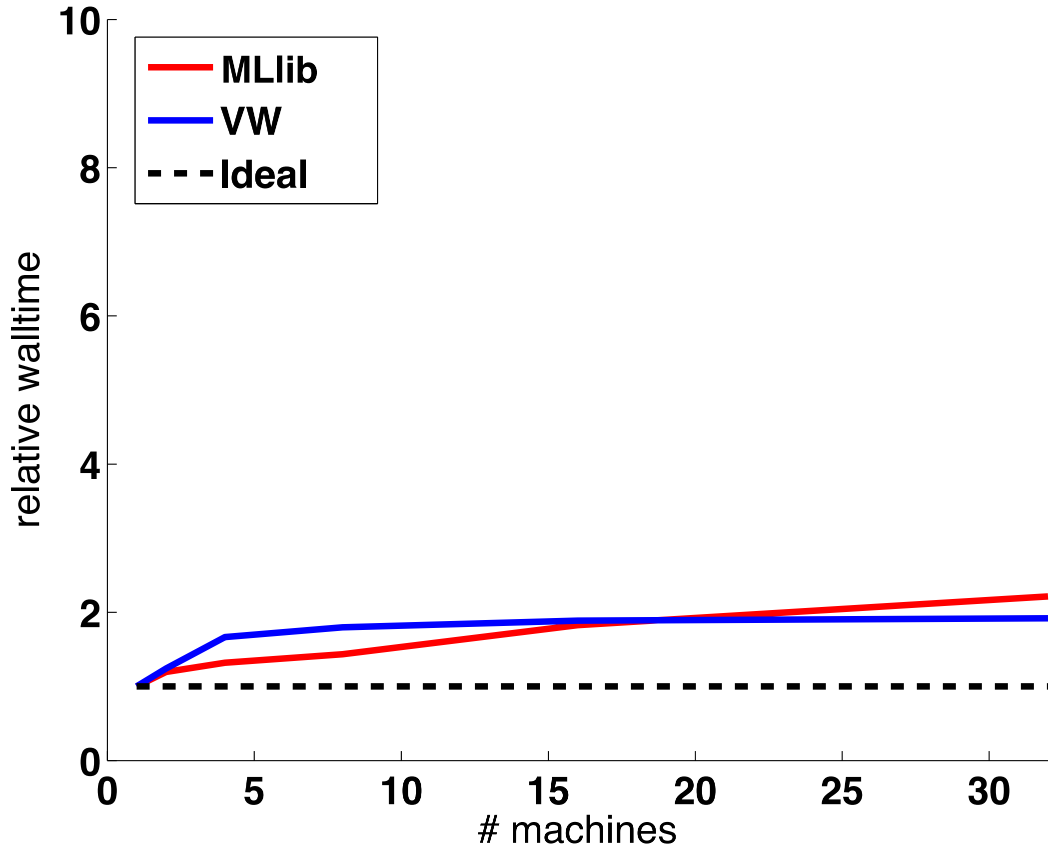
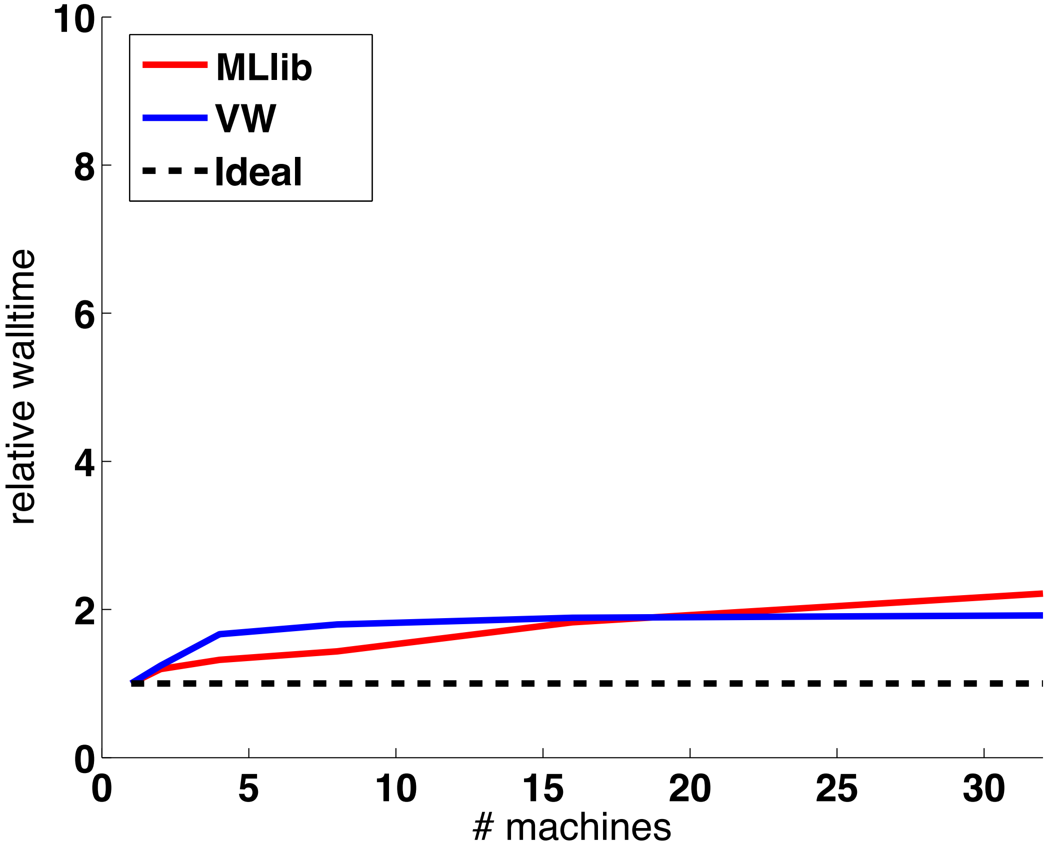
- Full dataset: 200K images, 160K dense features

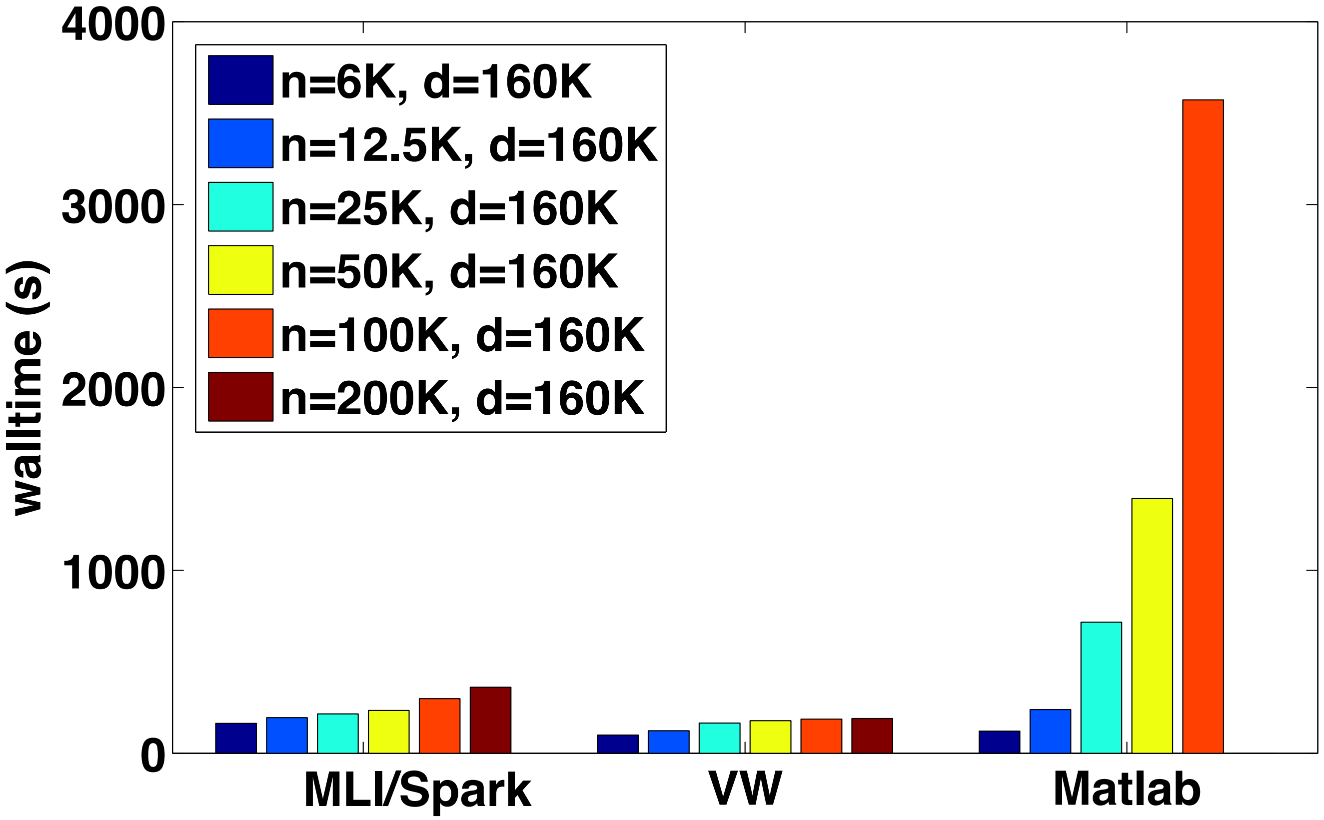
Logistic Regression - Weak Scaling



- ✦ Full dataset: 200K images, 160K dense features
- ✦ Similar weak scaling

Logistic Regression - Weak Scaling





- Full dataset: 200K images, 160K dense features
- Similar weak scaling
- MLI/Spark within a factor of 2 of VW's walltime

Logistic Regression - Strong Scaling

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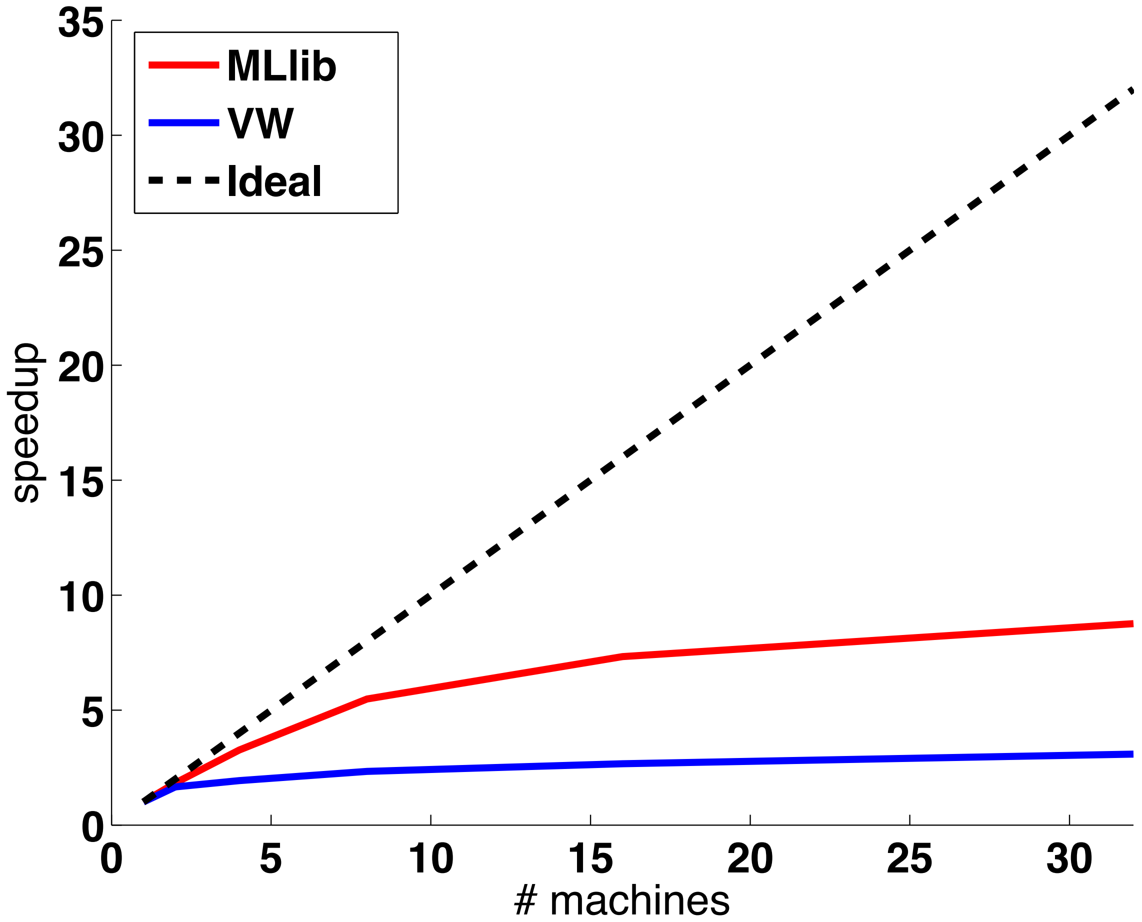
- Fixed Dataset: 50K images, 160K dense features

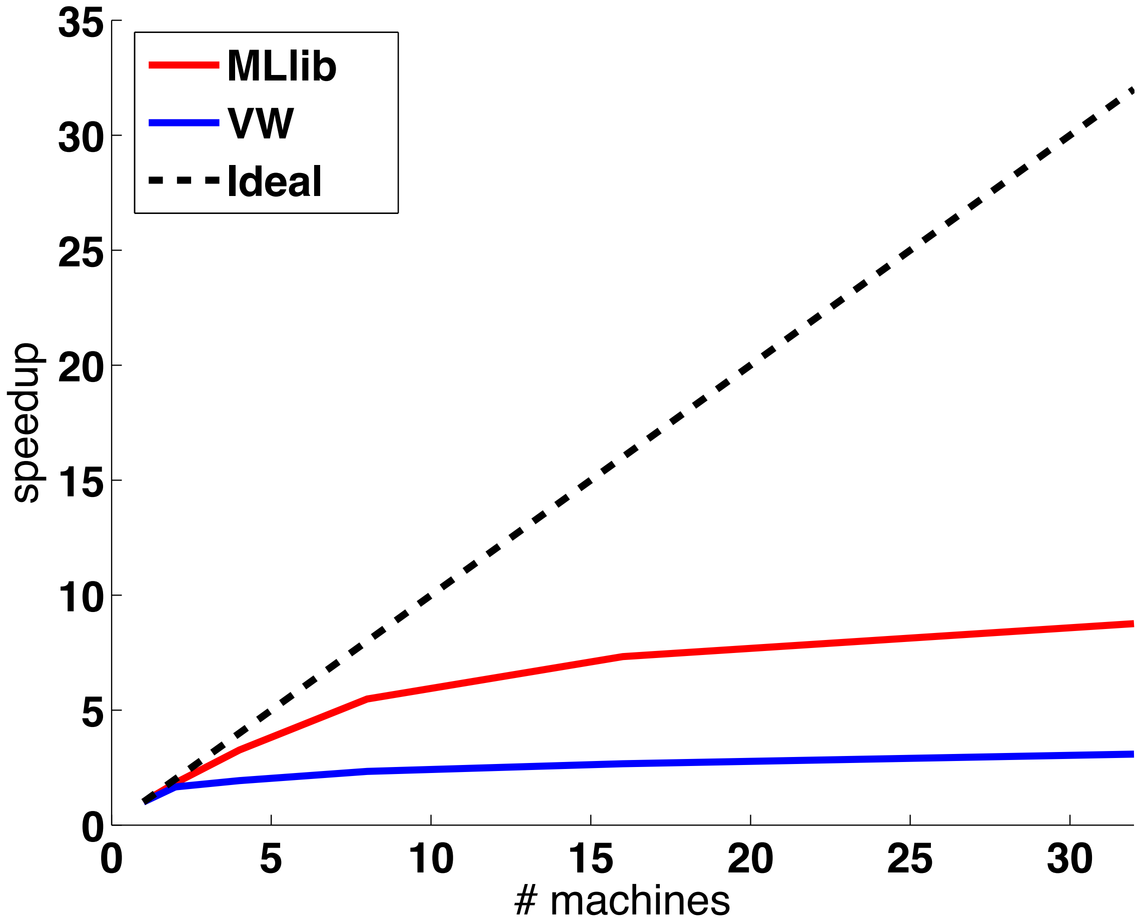
Logistic Regression - Strong Scaling

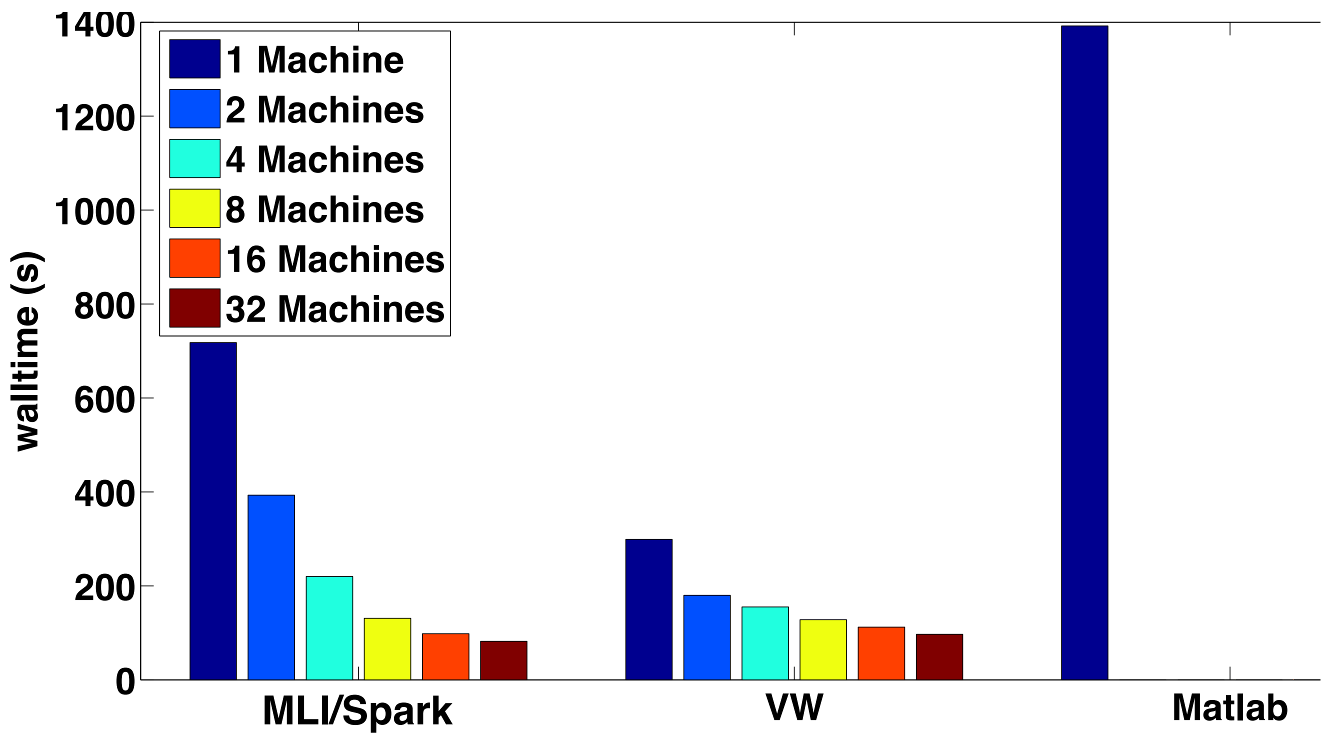


✦ Fixed Dataset: 50K images, 160K dense features

✦ MLI/Spark exhibits better scaling properties

Logistic Regression - Strong Scaling





- Fixed Dataset: 50K images, 160K dense features
- MLI/Spark exhibits better scaling properties
- MLI/Spark faster than VW with 16 and 32 machines

ALS - Walltime

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- Dataset: Scaled version of Netflix data (9X in size)
- Cluster: 9 machines

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System	Walltime (seconds)
Matlab	15443

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Matlab	15443
Mahout	4206
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MLI/Spark	481

- Dataset: Scaled version of Netflix data (9X in size)
- Cluster: 9 machines
- MLI/Spark an order of magnitude faster than Mahout
- MLI/Spark within factor of 2 of GraphLab

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MLI Functionality

Regression: Linear Regression (+Lasso, Ridge)

Collaborative Filtering: Alternating Least Squares

Clustering: K-Means

Classification: Logistic Regression, Linear SVM (+L1, L2)

Optimization Primitives: Parallel Gradient

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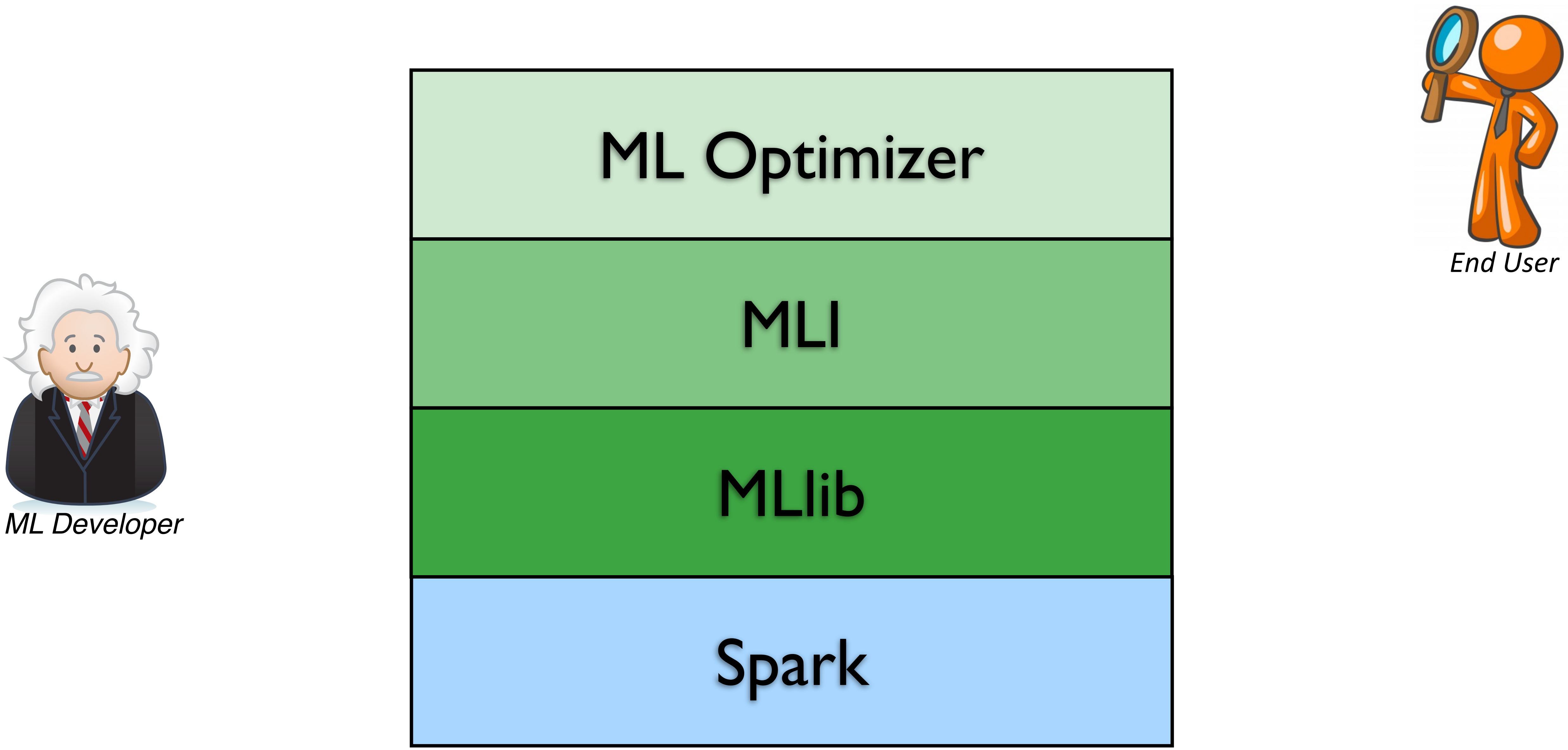
Collaborative Filtering:	Alternating Least Squares, DFC
Clustering:	K-Means, DP-Means
Classification:	Logistic Regression, Linear SVM (+L1, L2), Multinomial Regression, Naive Bayes, Decision Trees
Optimization Primitives:	Parallel Gradient, Local SGD, L-BFGS, ADMM, Adagrad
Feature Extraction:	Principal Component Analysis (PCA), N-grams, feature normalization
ML Tools:	Cross Validation, Evaluation Metrics

MLbase Stack Status



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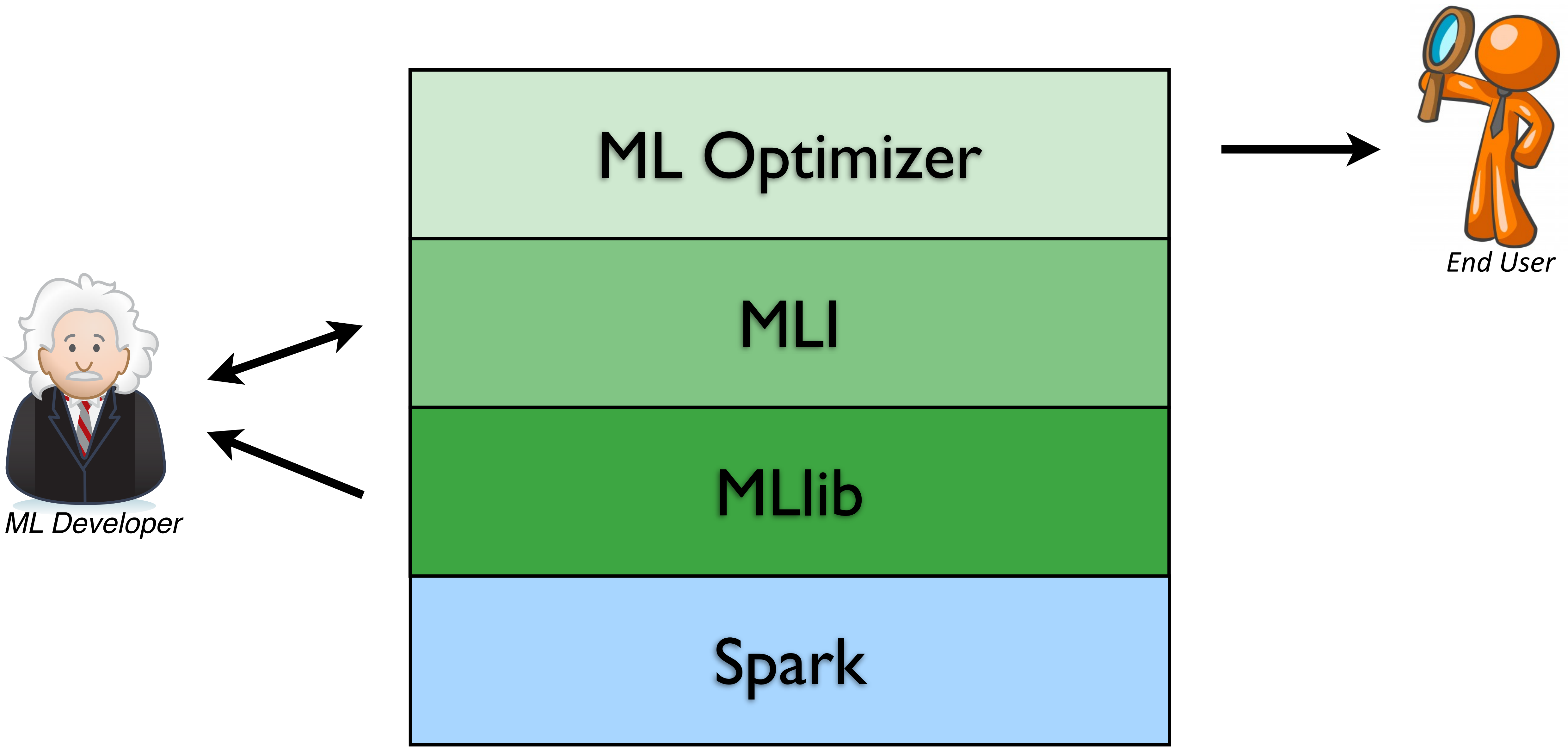

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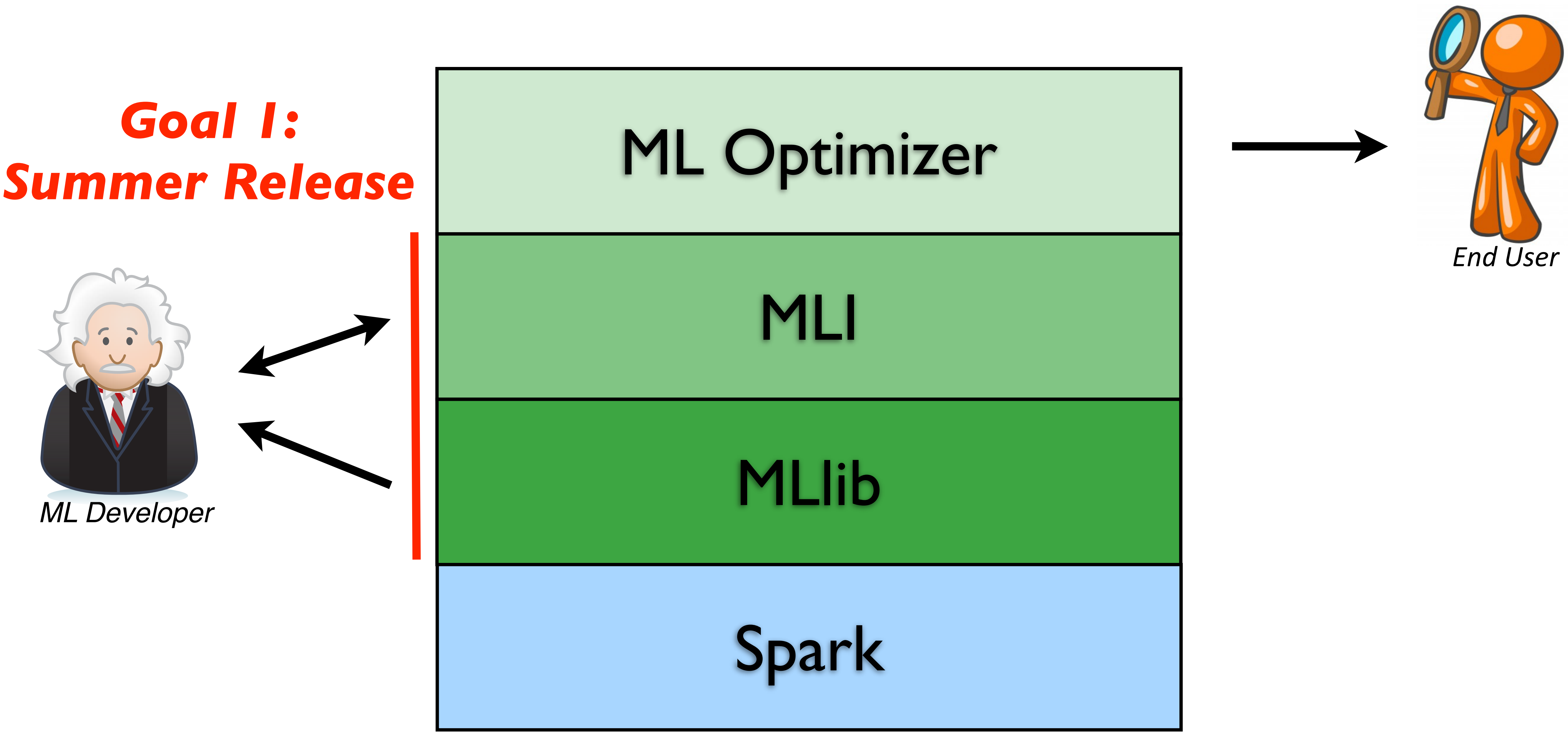
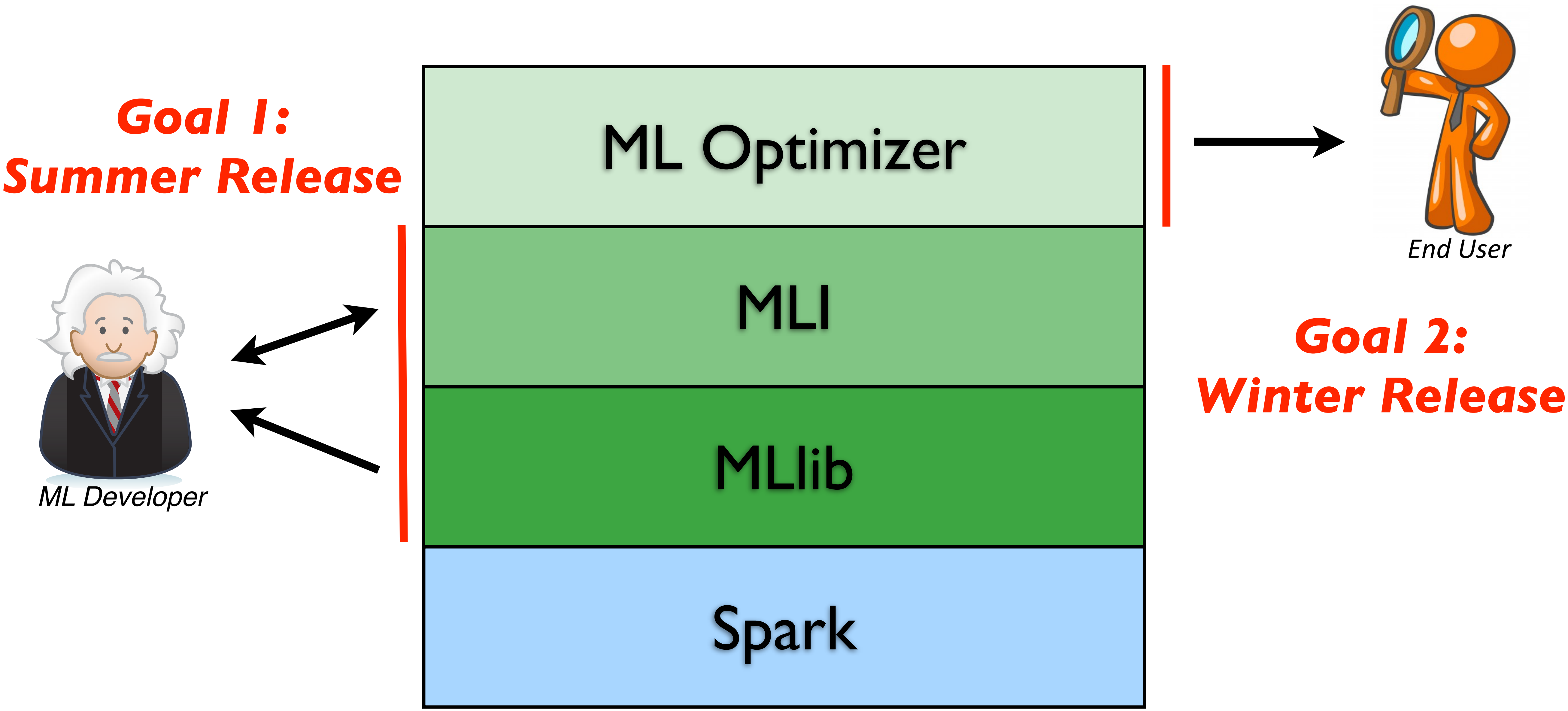


MLbase Stack Status



Future Directions

- **Identify minimal set of ML operators**
  - Expose internals of ML algorithms to optimizer
- Plug-ins to **Python, R**
- **Visualization** for unsupervised learning and exploration
- **Advanced ML capabilities**
  - Time-series algorithms
  - Graphical models
  - Advanced Optimization (e.g., asynchronous computation)
  - Online updates
  - Sampling for efficiency

Vision

MLI Details

Current Status

ML Workflow

Typical Data Analysis Workflow

Adapted from slides by Ariel Kleiner

Typical Data Analysis Workflow

Spark, MLI **Obtain / Load Raw Data**

Adapted from slides by Ariel Kleiner

Typical Data Analysis Workflow

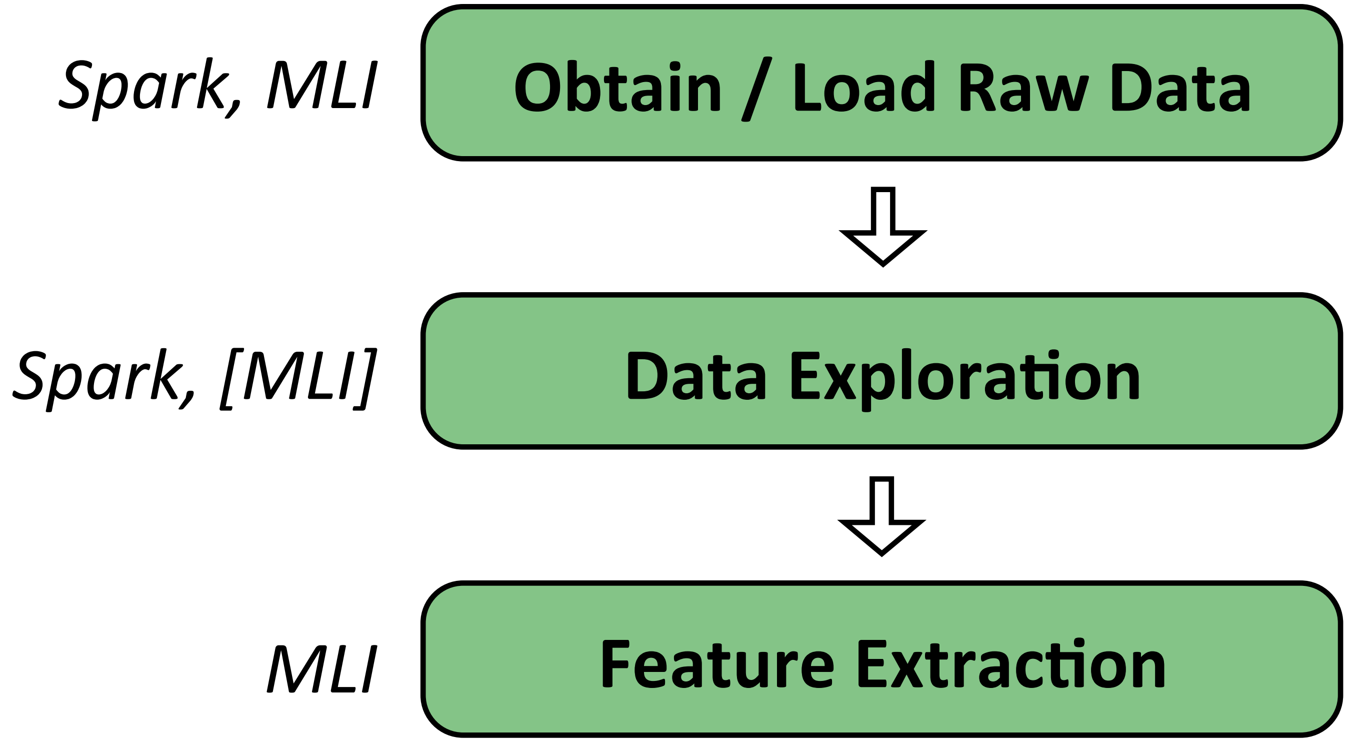
Spark, MLI — **Obtain / Load Raw Data**

⇩

Spark, [MLI] — **Data Exploration**

Adapted from slides by Ariel Kleiner

Typical Data Analysis Workflow



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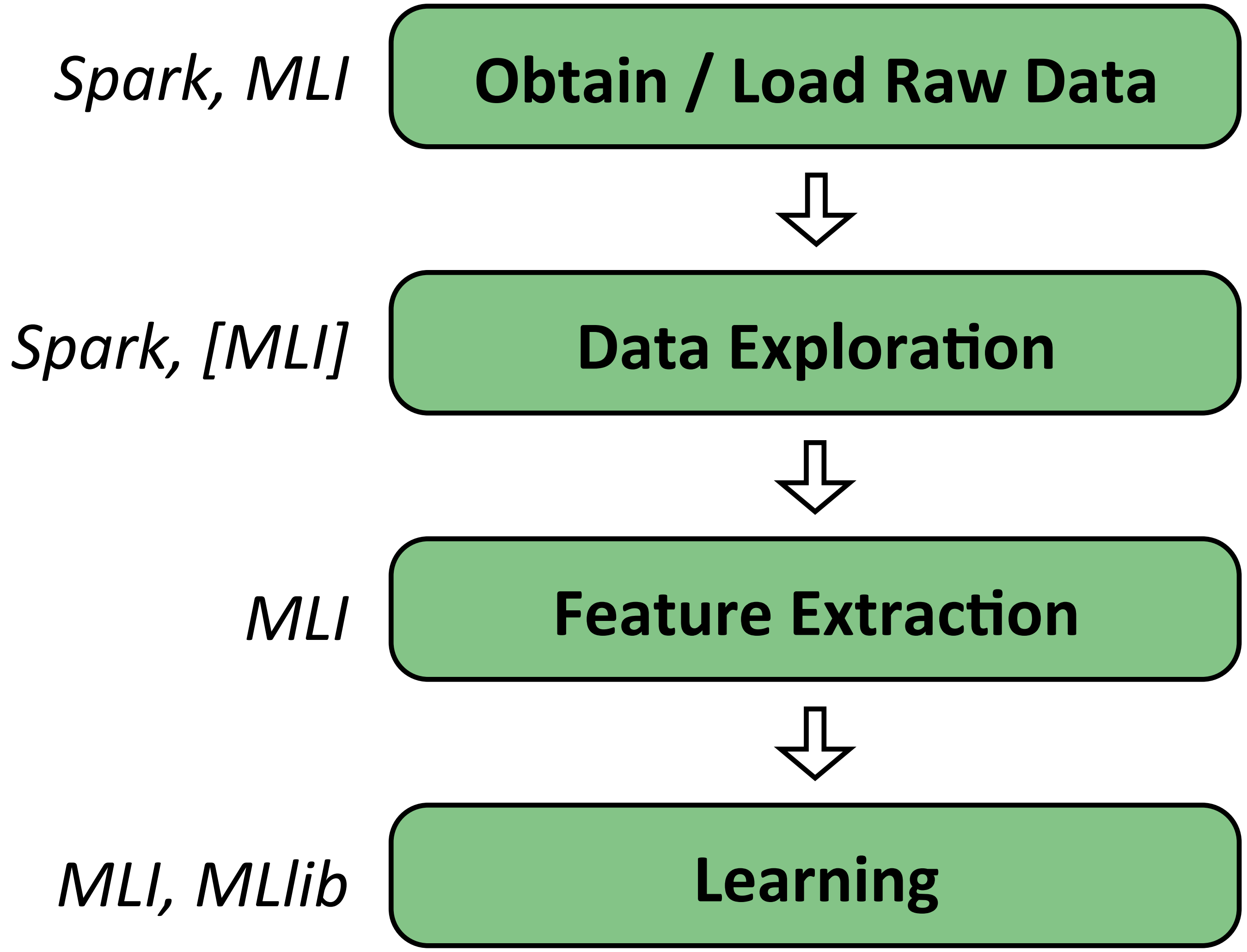

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Typical Data Analysis Workflow

Tools	Step
Spark, MLI	**Obtain / Load Raw Data**
Spark, [MLI]	**Data Exploration**
MLI	**Feature Extraction**
MLI, MLlib	**Learning**
MLI	**Evaluation**

Adapted from slides by Ariel Kleiner

Typical Data Analysis Workflow

Spark, MLI	**Obtain / Load Raw Data**
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Scala	**Deployment**

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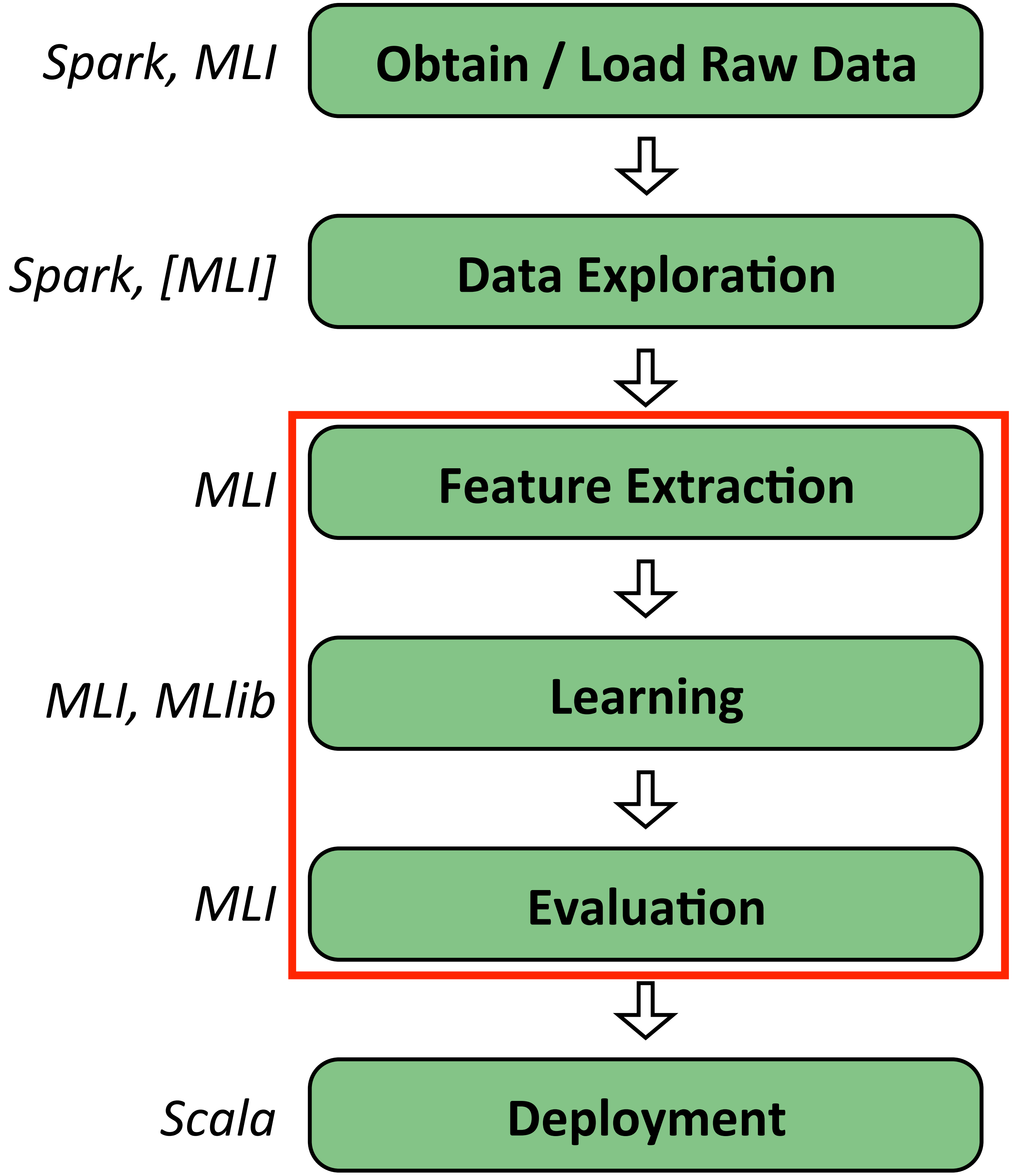
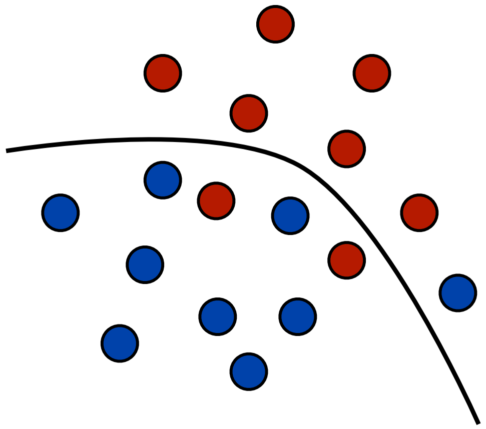
Typical Data Analysis Workflow



Adapted from slides by Ariel Kleiner

Binary Classification



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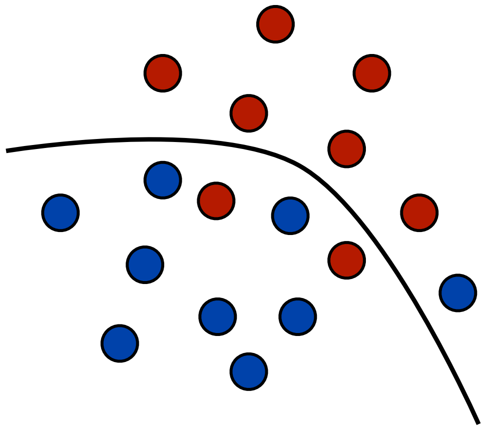

Goal: Learn a mapping from entities to discrete labels

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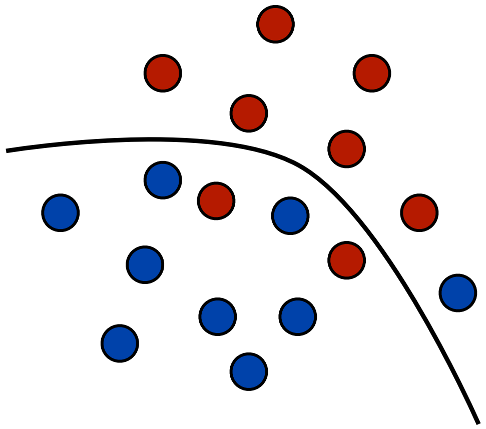
Binary Classification

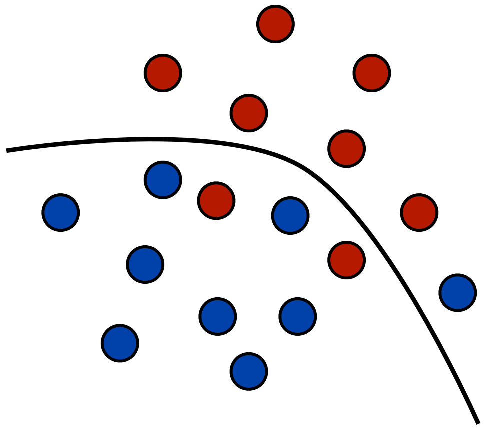


Goal: Learn a mapping from entities to discrete labels

Example: Spam Classification

- Entities are emails
- Labels are {*spam*, *not-spam*}

Binary Classification



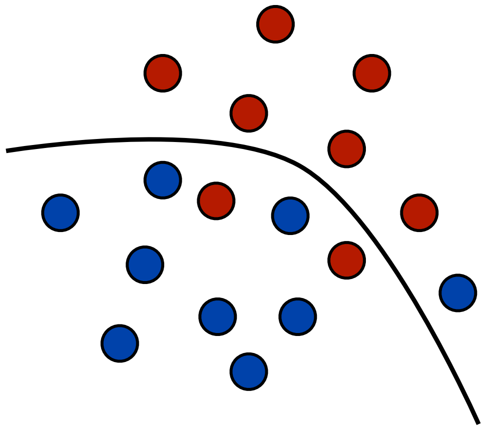
Goal: Learn a mapping from entities to discrete labels

Example: Spam Classification

- Entities are emails
- Labels are {*spam*, *not-spam*}
- Given past labeled emails, we want to predict whether a new email is *spam* or *not-spam*

Adapted from slides by Ariel Kleiner

Binary Classification

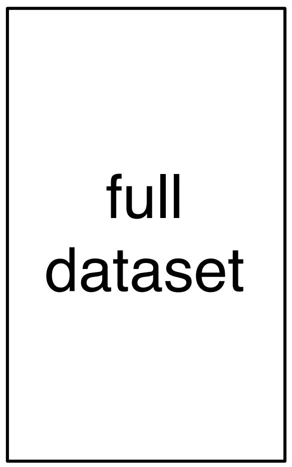


Goal: Learn a mapping from entities to discrete labels

Other Examples:

- Click (and clickthrough rate) prediction
- Fraud detection
- Face detection
- Exercise: "ARTS" vs "LIFE" on Wikipedia
  - Real data

Classification Pipeline



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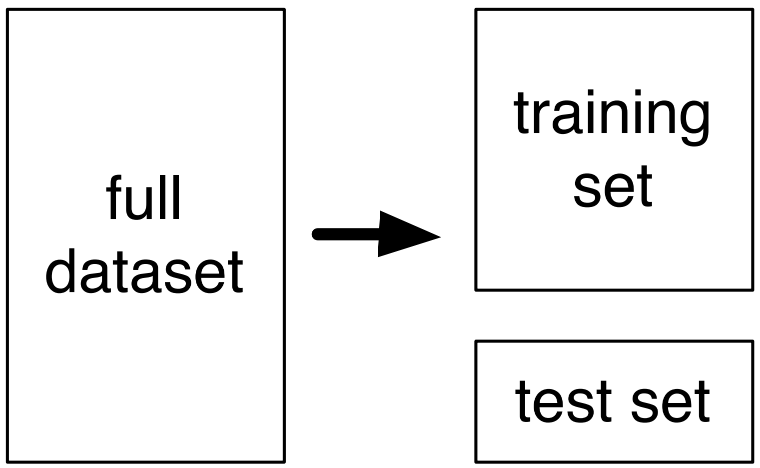
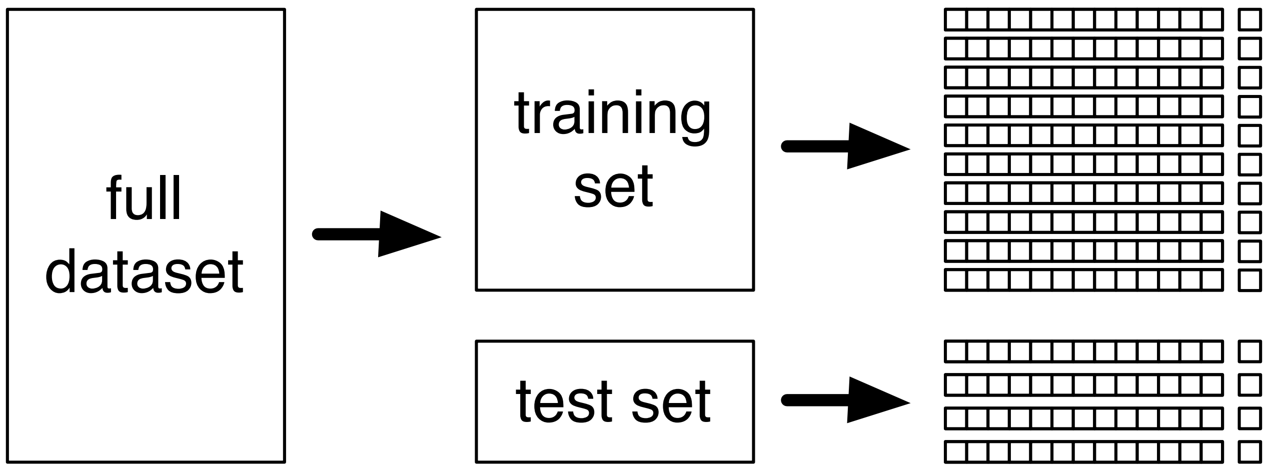
Classification Pipeline



1. Randomly split full data into disjoint subsets

Adapted from slides by Ariel Kleiner

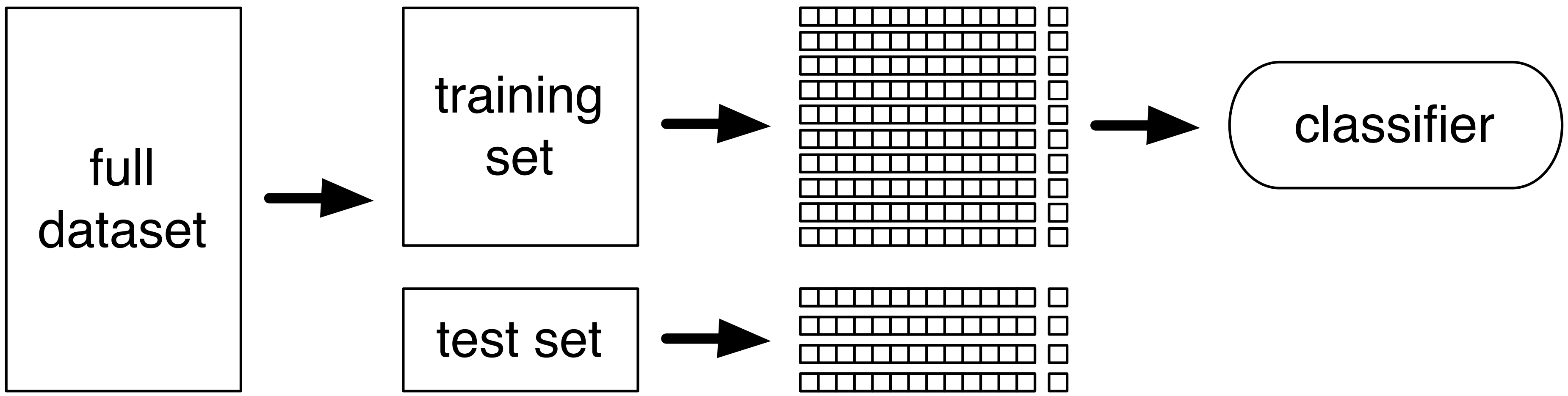
Classification Pipeline



1. Randomly split full data into disjoint subsets
2. Featurize the data

Adapted from slides by Ariel Kleiner

Classification Pipeline



1. Randomly split full data into disjoint subsets
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3. Use training set to learn a classifier

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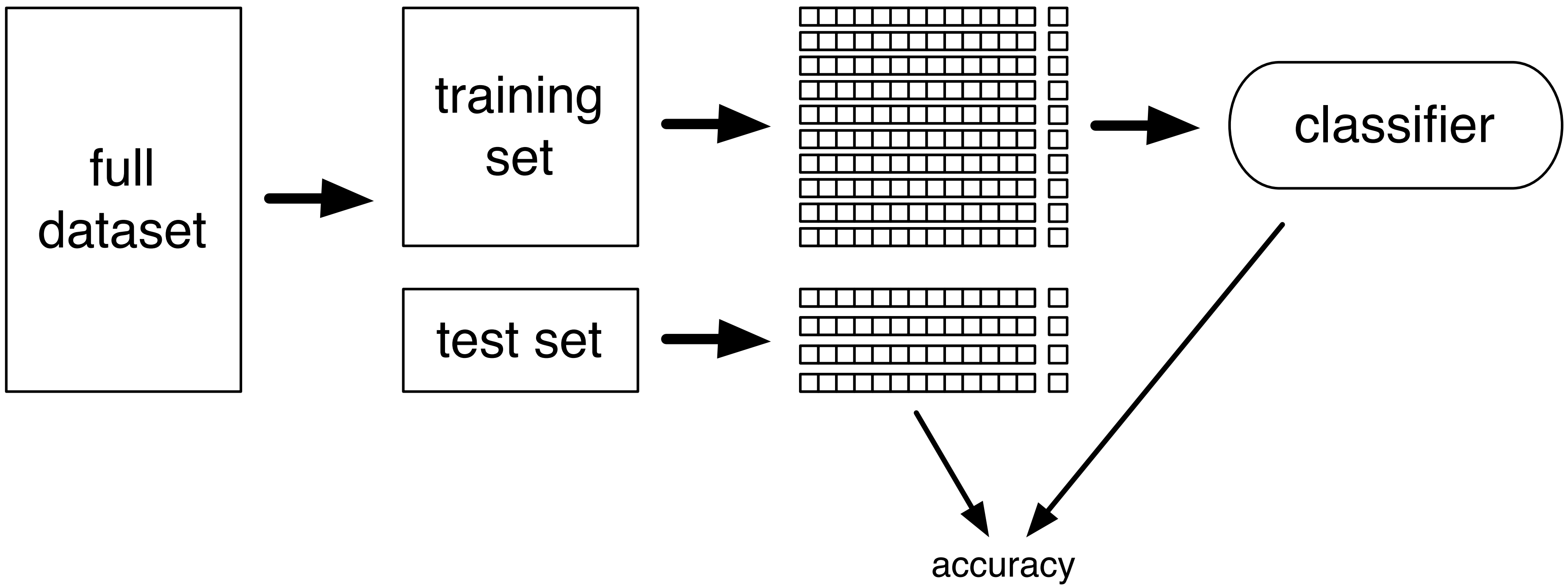

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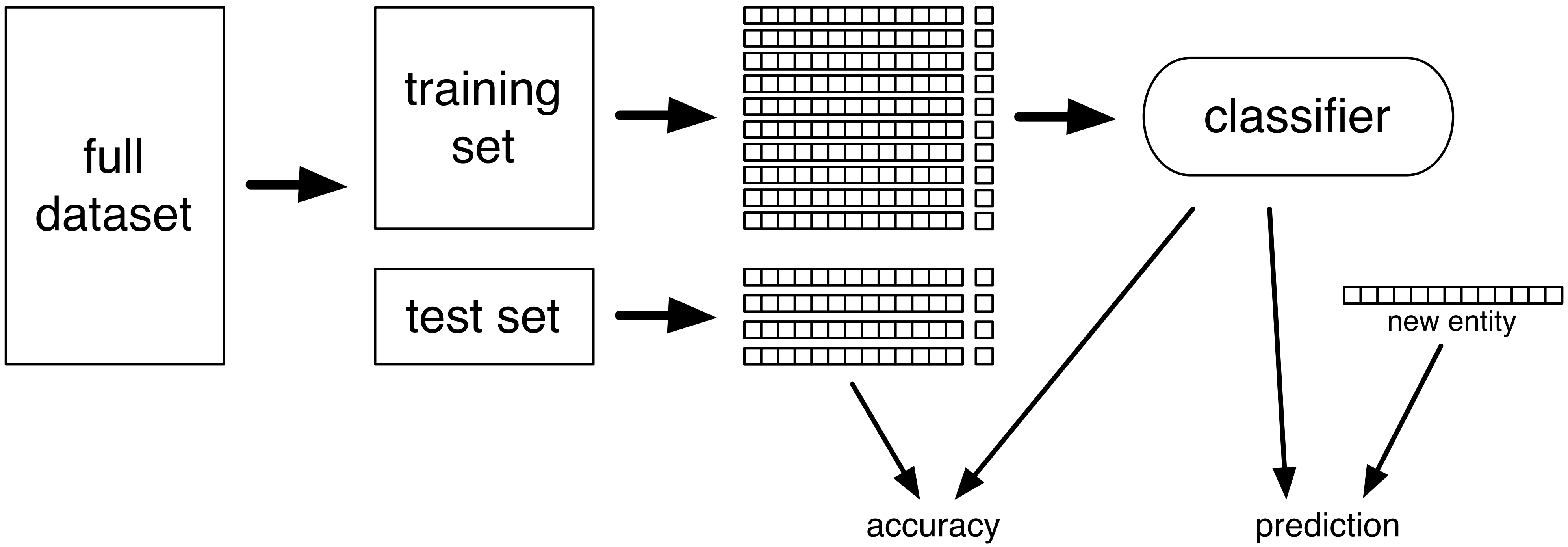
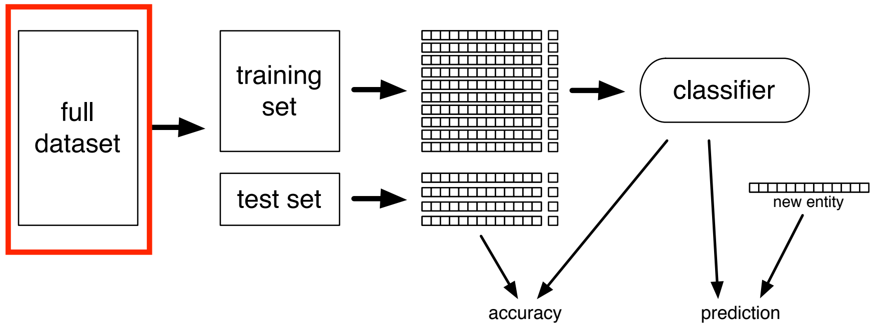


1. Randomly split full data into disjoint subsets
2. Featurize the data
3. Use training set to learn a classifier
4. Evaluate classifier on test set (avoid overfitting)
5. Use classifier to predict in the wild

Adapted from slides by Ariel Kleiner

E.g., Spam Classification




```
From: illegitimate@bad.com

"Eliminate your debt by
giving us your money..."
```

spam

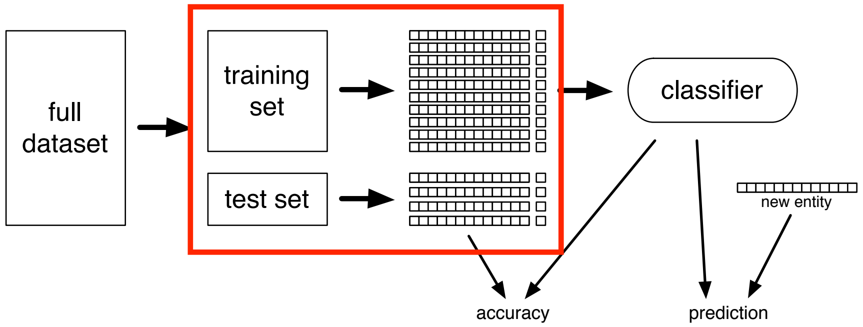
```
From: bob@good.com

"Hi, it's been a while!
How are you? ..."
```

not-spam

Adapted from slides by Ariel Kleiner

Featurization



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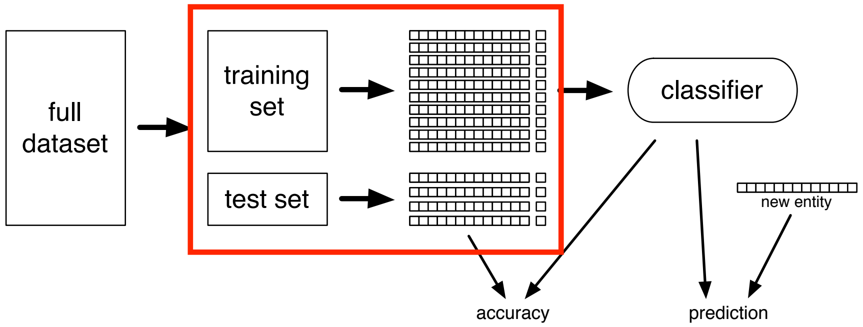
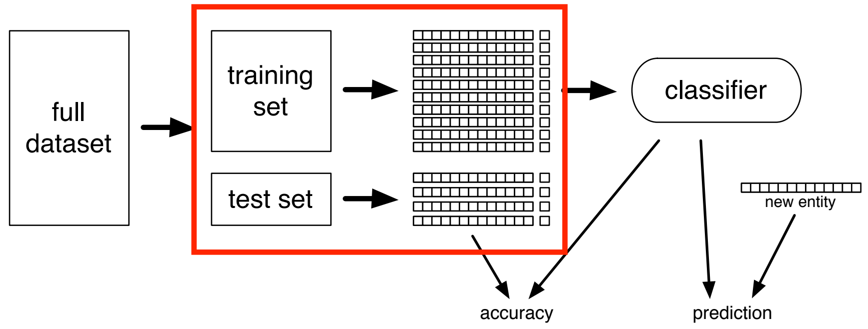
Featurization



- Most classifiers require numeric descriptions of entities

Featurization



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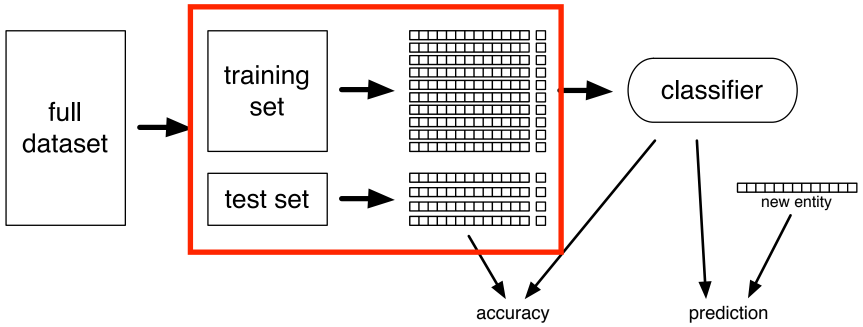
- **Featurization**: Transform each entity into a vector of real numbers

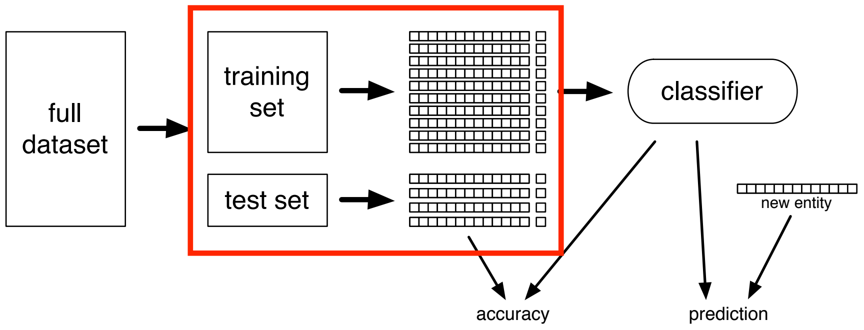
Featurization



- Most classifiers require numeric descriptions of entities

- **Featurization**: Transform each entity into a vector of real numbers
  - Opportunity to incorporate domain knowledge
  - Useful even when original data is already numeric

E.g., “Bag of Words”

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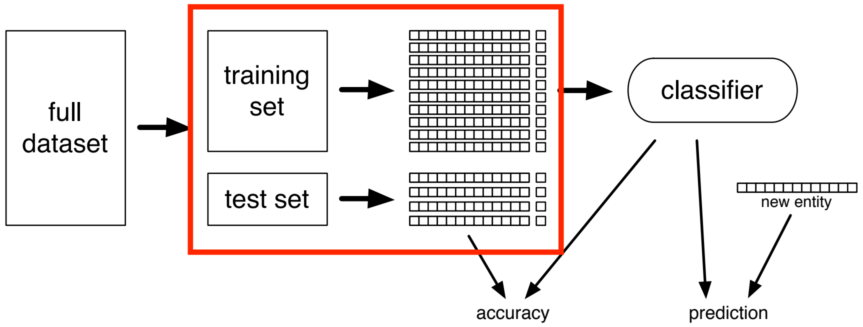

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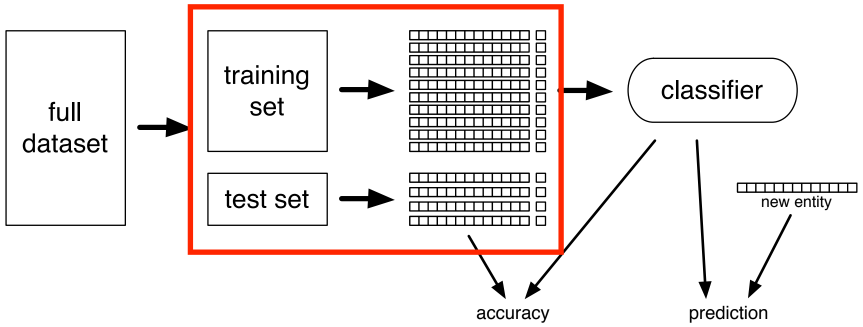

- Entities are documents
- Build Vocabulary

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Vocabulary

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debt
eliminate
giving
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```

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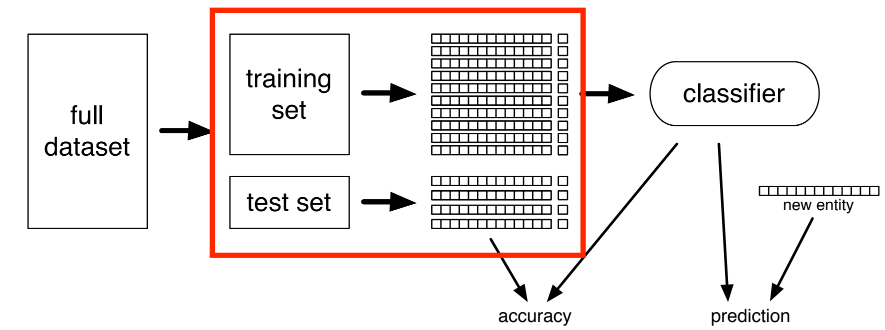
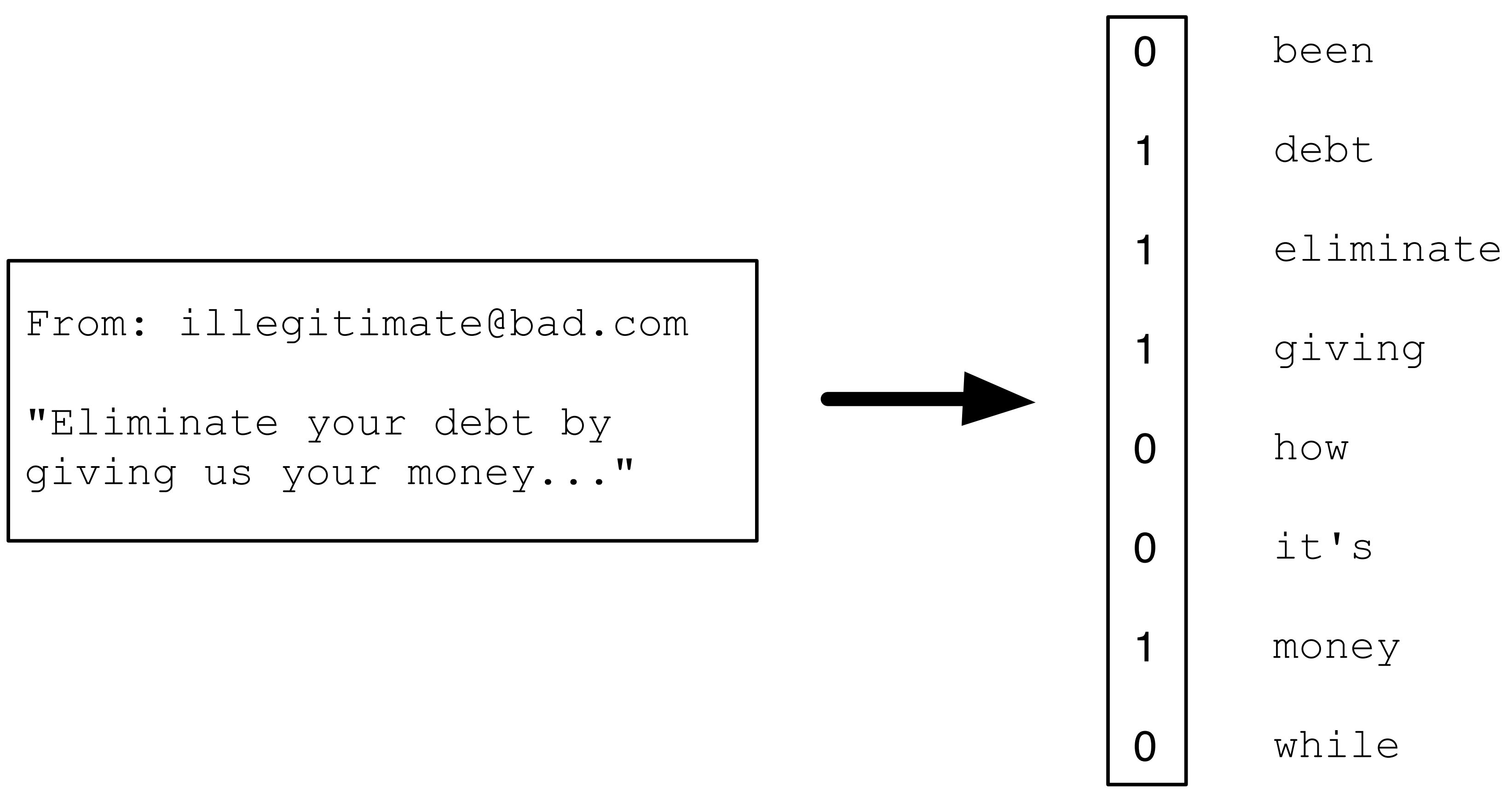
E.g., "Bag of Words"



- Entities are documents
- Build Vocabulary
- Derive feature vectors from Vocabulary
  - Exercise: we'll use *bigrams*



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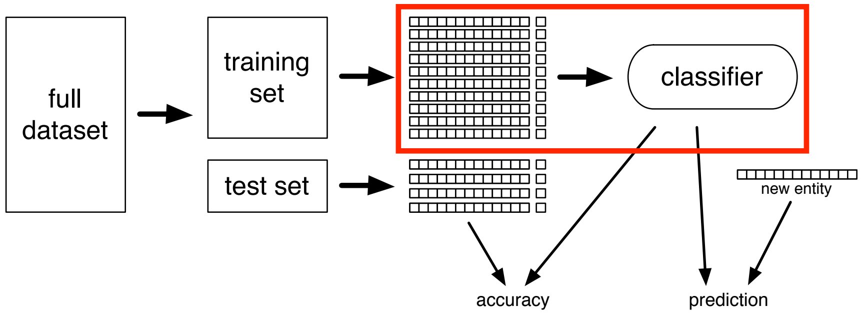
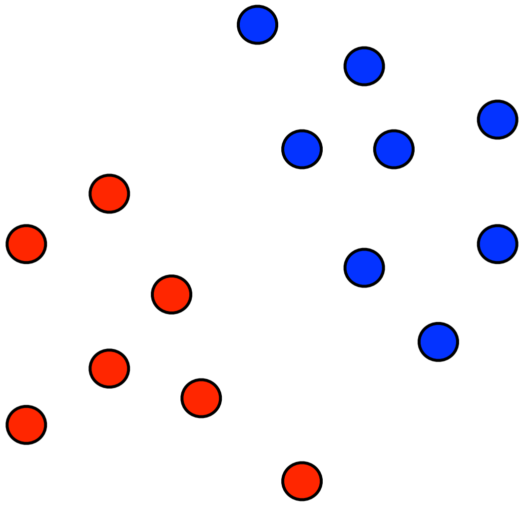
Support Vector Machines (SVMs)





Credit: Foundations of Machine Learning
Mohri, Rostamizadeh, Talwalkar

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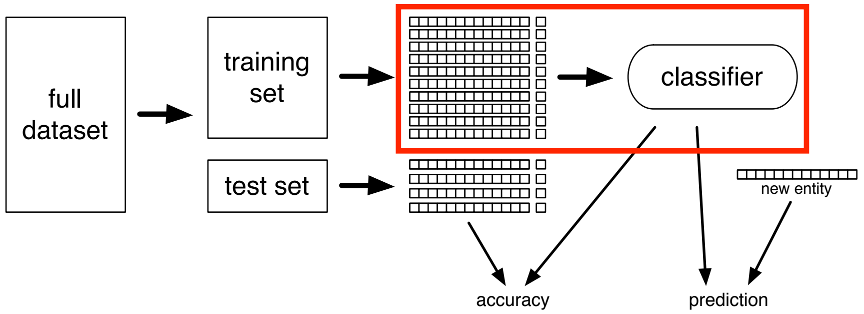

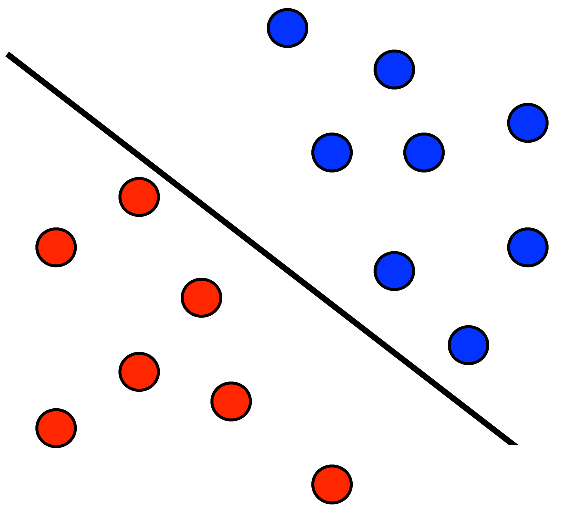

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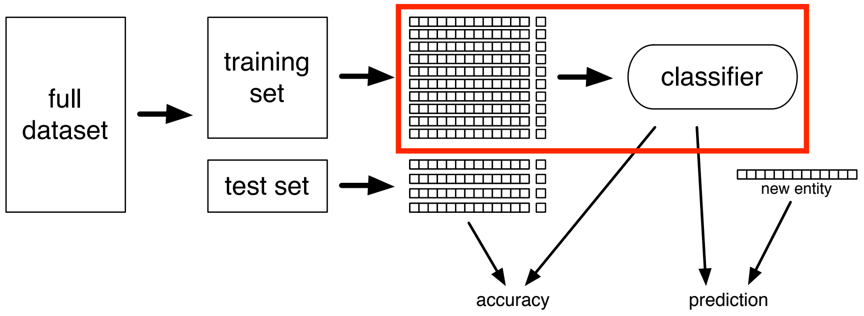

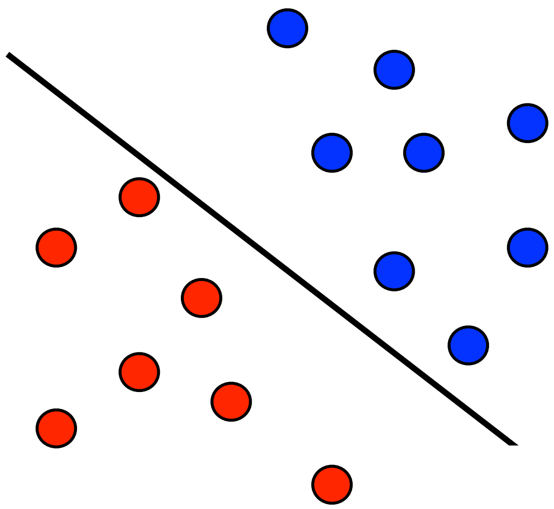

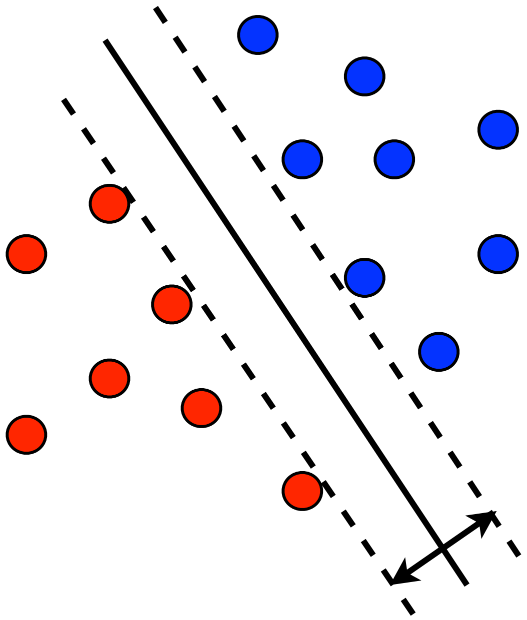

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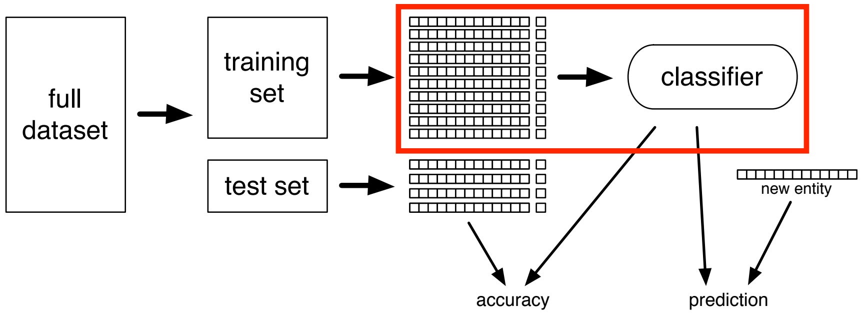
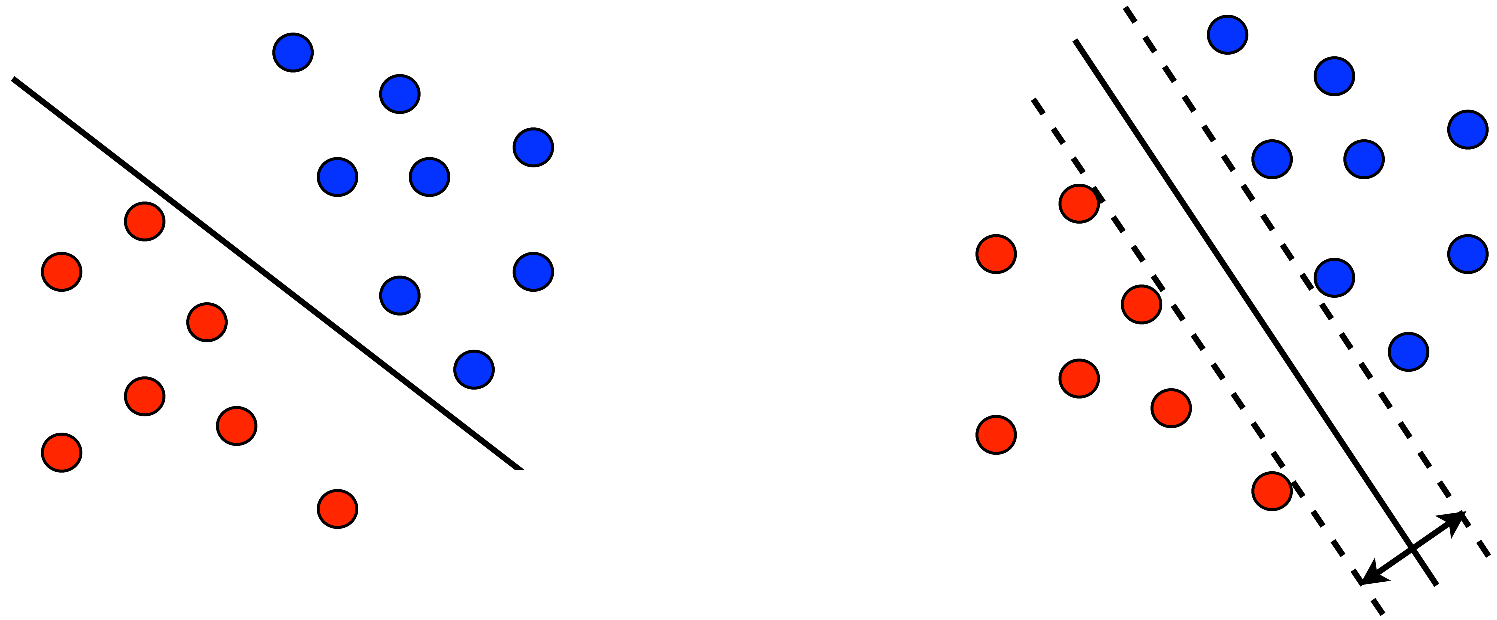


- "Max-Margin": find linear separator with the largest separation between the two classes



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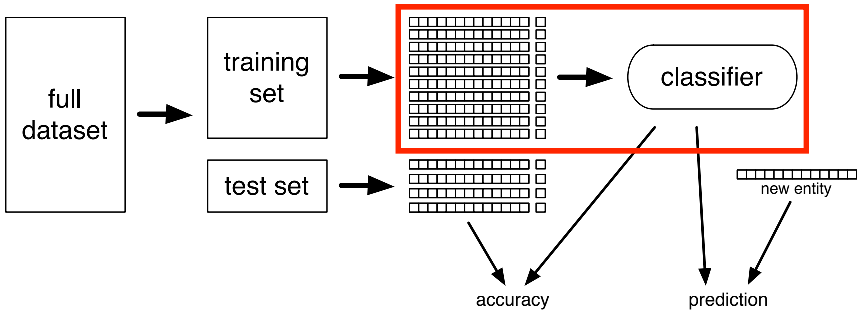
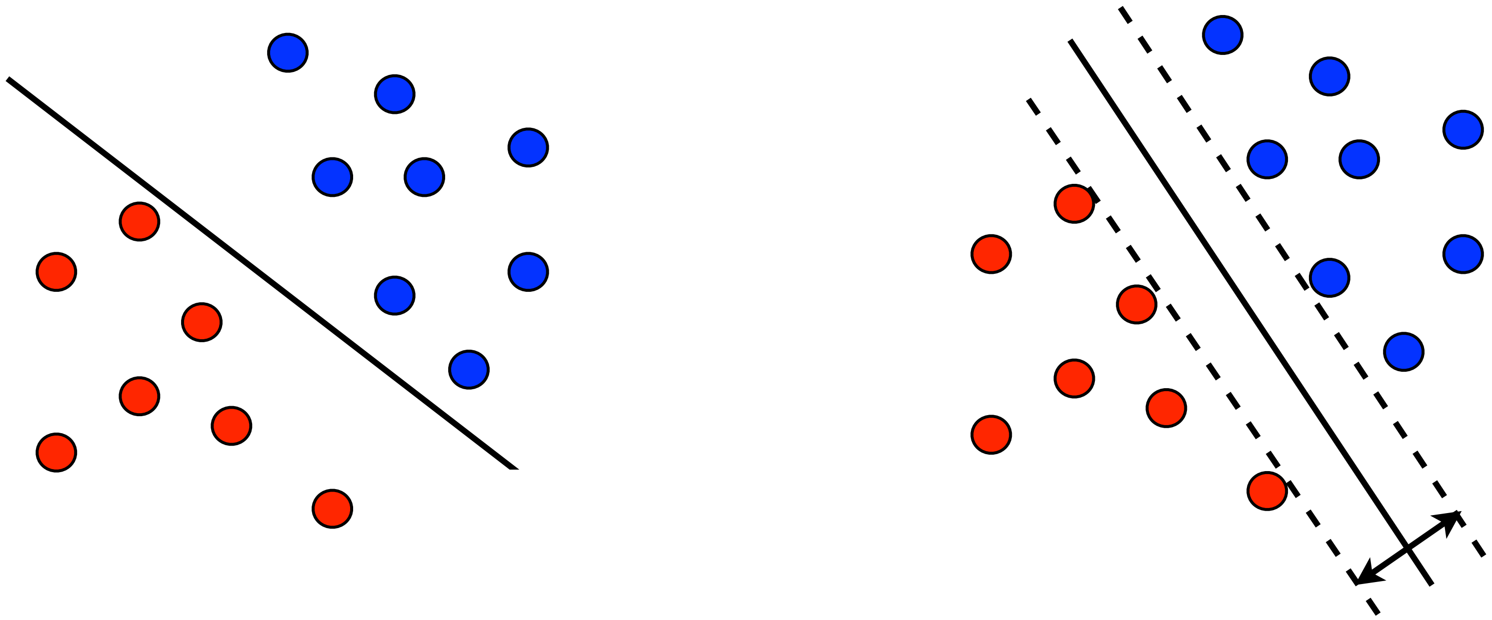


- "Max-Margin": find linear separator with the largest separation between the two classes
- Extensions:
  - non-separable setting
  - non-linear classifiers (kernels)



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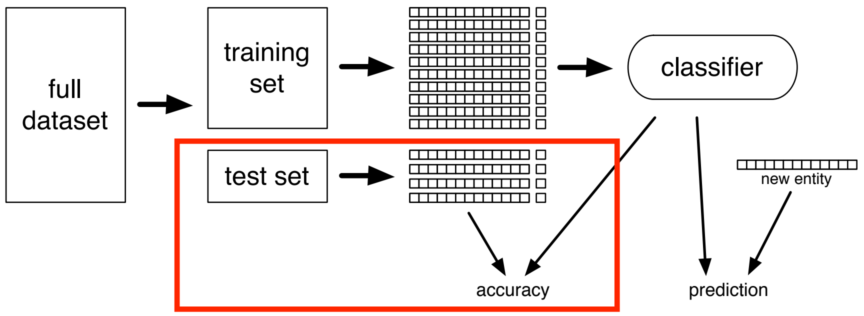
Model Evaluation



Adapted from slides by Ariel Kleiner

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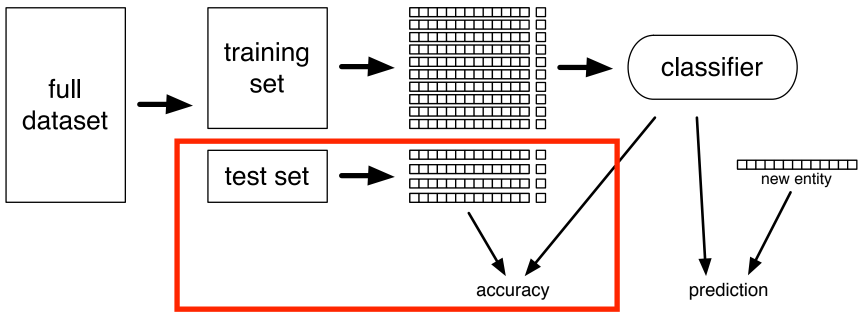

- Test set simulates performance on new entity
  - Performance on training data overly optimistic!
  - "Overfitting"; "Generalization"

Adapted from slides by Ariel Kleiner

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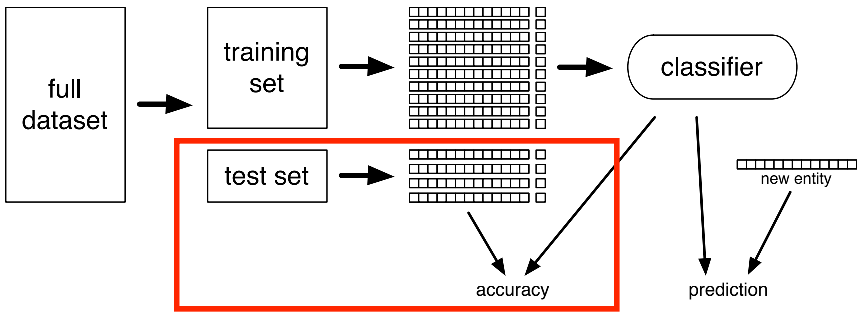

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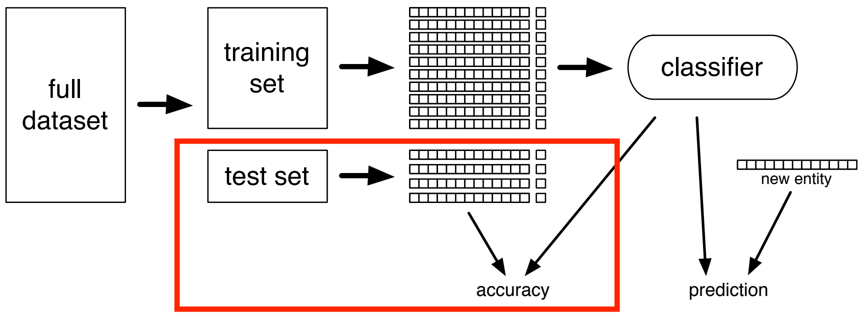

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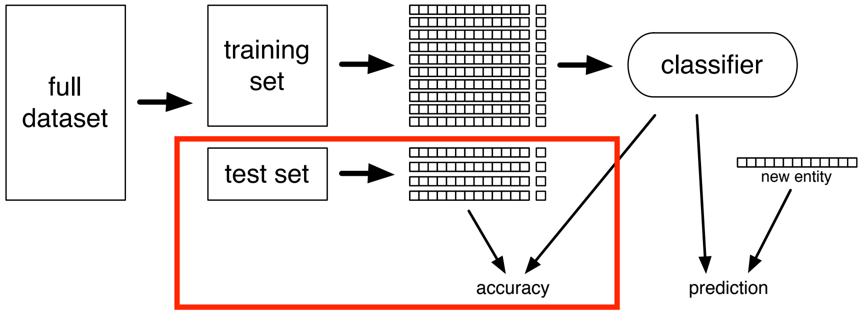

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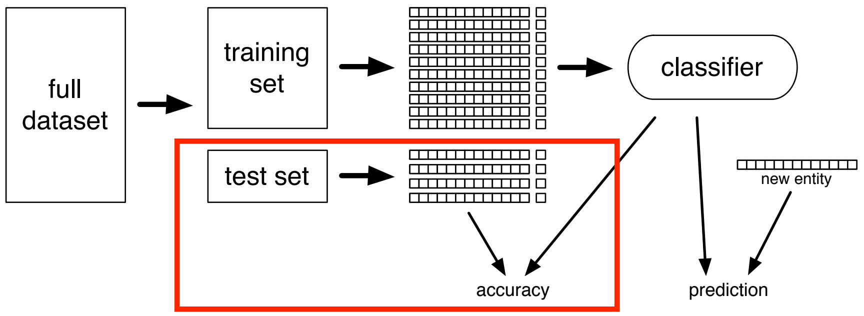

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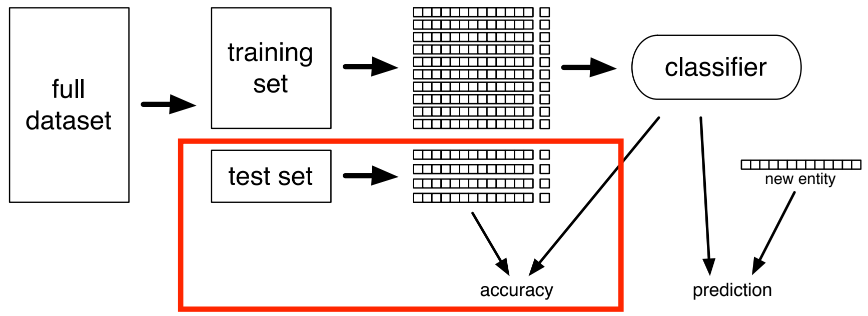

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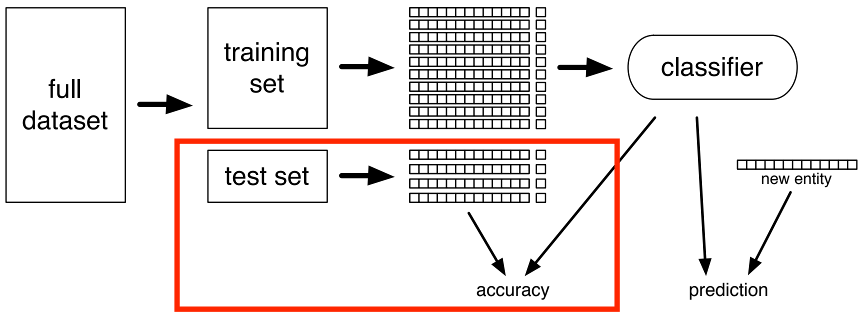

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  - Compute fraction of correct predictions on test set
- Other more sophisticated evaluation methods, e.g., cross-validation

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Contributions encouraged!

MLbase

www.mlbase.org

SIMONS INSTITUTE for the Theory of Computing

biglearn.org