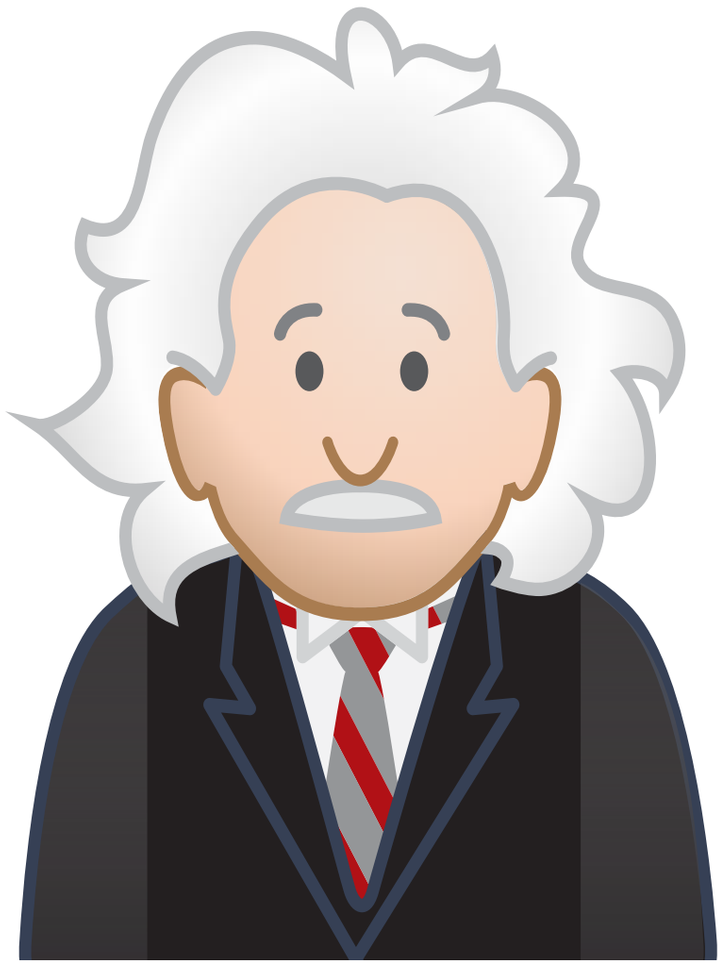
Towards an Optimizer for MLbase

Ameet Talwalkar

Collaborators: Evan Sparks, Michael Franklin, Michael I. Jordan, Tim Kraska

Problem: Scalable implementations *difficult* for ML Developers…



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DATABRICKS

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VOWPAL WABBIT

mahout

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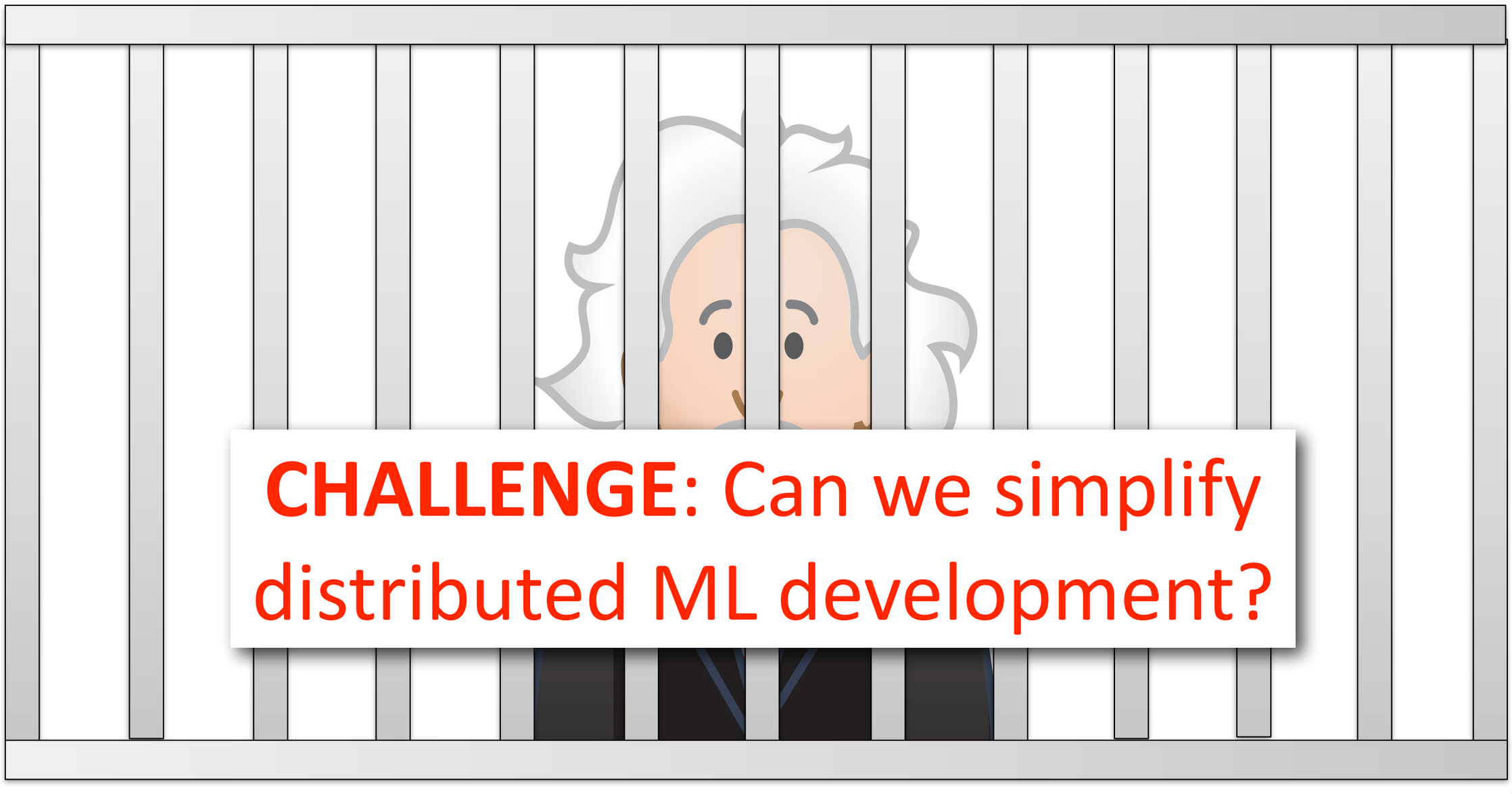

CHALLENGE: Can we simplify distributed ML development?

Problem: ML is *difficult* for End Users…

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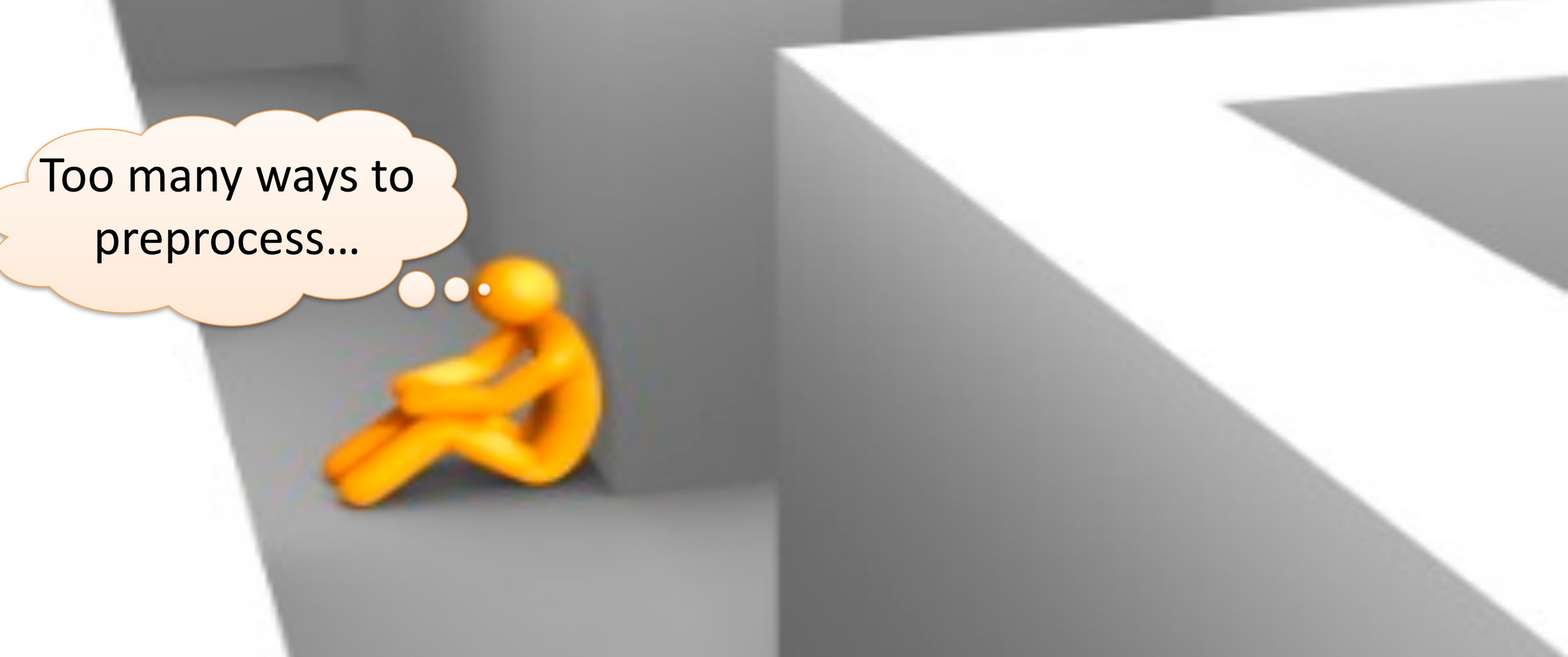

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Too many algorithms…

Too many ways to preprocess…

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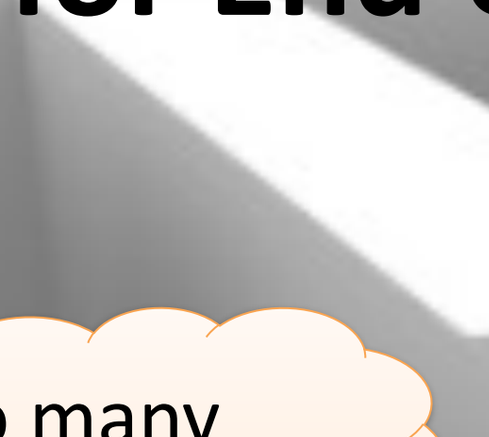

Difficult to debug…

Doesn’t scale…

Problem: ML is *difficult* for End Users…

Too many algorithms…

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Difficult to debug

CHALLENGE: Can we automate ML pipeline construction?

MLbase

MLbase aims to simplify development and deployment of ML pipelines

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Apache Spark

Spark: Cluster computing system designed for iterative computation

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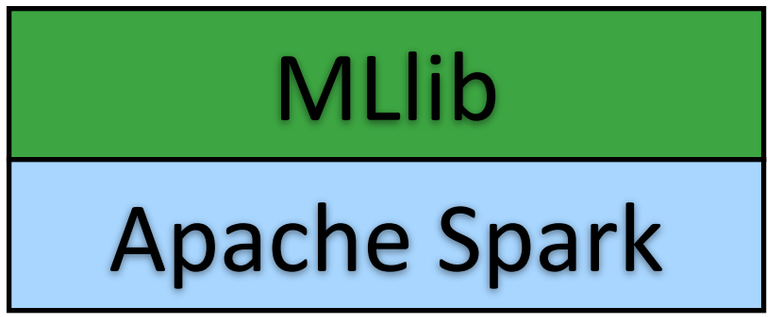

Spark: Cluster computing system designed for iterative computation

MLlib: Spark's core ML library

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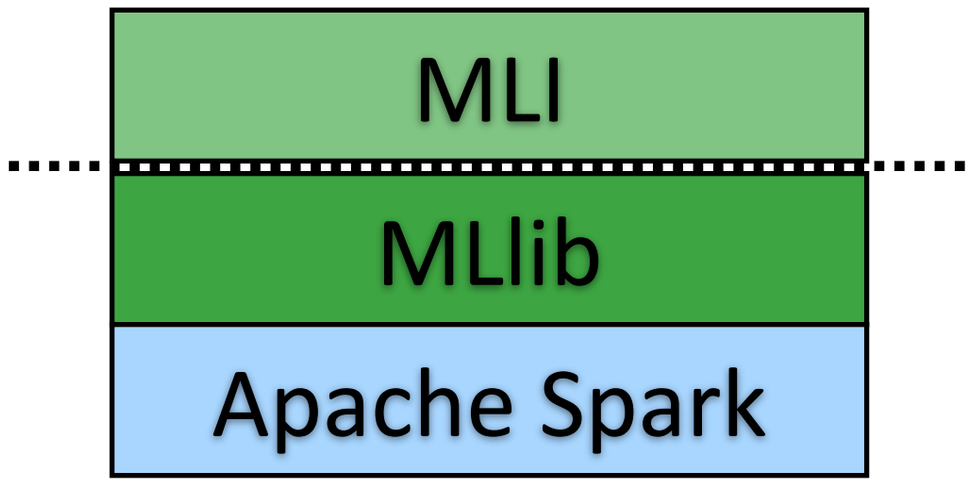

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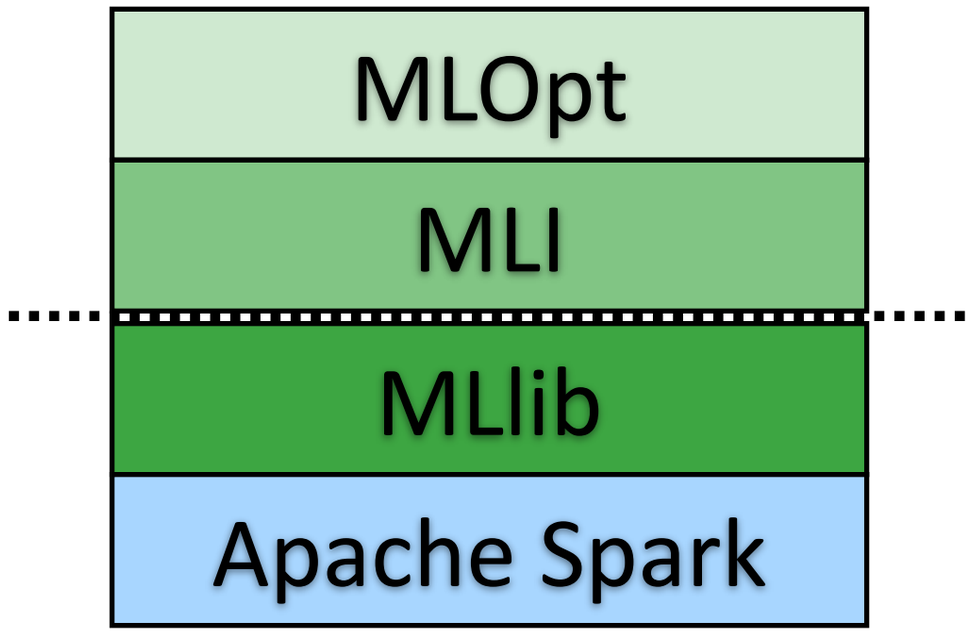

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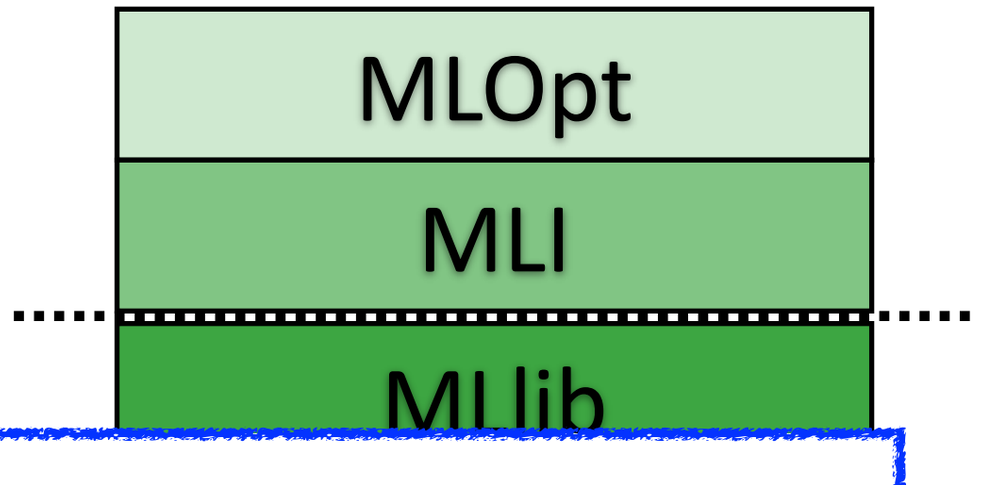

MLOpt and MLI are experimental testbeds

Spark: ...ation

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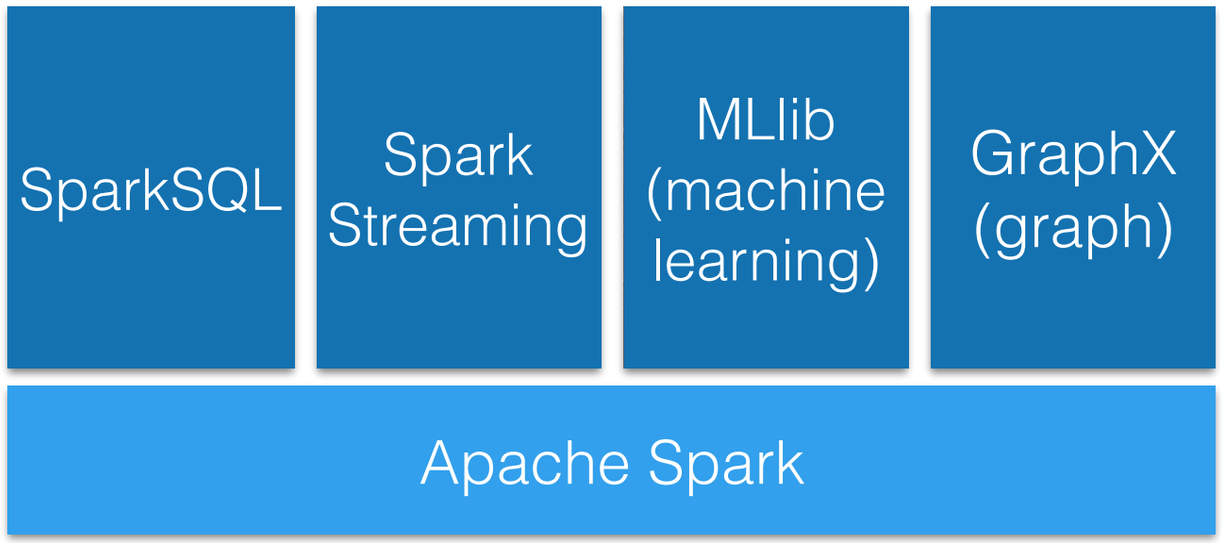
Vision

MLlib and MLI

MLOpt

MLlib

+ Scalable and fast
+ Simple development environment
+ Part of Spark's robust ecosystem



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Initial Release

- Developed by MLbase team in AMPLab (11 contributors)
- Scala, Java
- Shipped with Spark v0.8 (Sep 2013)

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11 months later…

- 55+ contributors from various organizations
- Scala, Java, Python
- Improved documentation / code examples, API stability
- Latest release part of Spark v1.0 (May 2014)

Algorithms in v0.8

- **classification**: logistic regression, linear support vector machines (SVM)
- **regression**: linear regression,
- **collaborative filtering**: alternating least squares (ALS)
- **clustering**: k-means
- **optimization**: stochastic gradient descent (SGD)

Algorithms in v1.0

- **classification**: logistic regression, linear support vector machines (SVM), naive Bayes, decision trees
- **regression**: linear regression, regression trees
- **collaborative filtering**: alternating least squares (ALS)
- **clustering**: k-means
- **optimization**: stochastic gradient descent (SGD), limited-memory BFGS (L-BFGS)
- **dimensionality reduction**: singular value decomposition (SVD), principal component analysis (PCA)

MLlib, MLI and Roadmap

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- MLI: Shield ML Developers from low-details
  - Provide familiar mathematical operators in distributed setting (tables, matrices, optimization primitives)
  - Standard APIs defining ML algorithms and feature extractors

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  - statistical toolbox, python decision tree API, online logistic regression, …

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  - Scalable implementations of standard ML algorithms and underlying optimization primitives
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Feedback and Contributions Encouraged!

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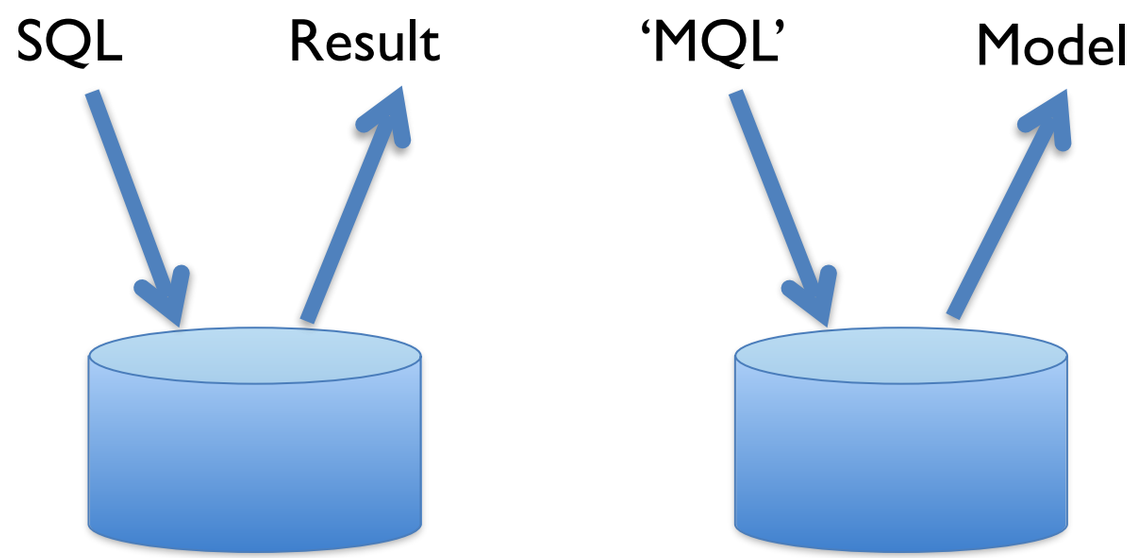
Vision

MLlib and MLI

MLOpt

DATABRICKS

Grand Vision



- User declaratively specifies a task
- Search through MLlib/MLI to find the best model/pipeline

DATABRICKS

A Standard ML Pipeline

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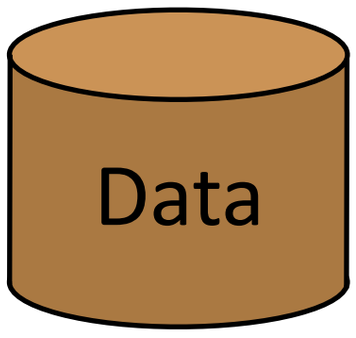

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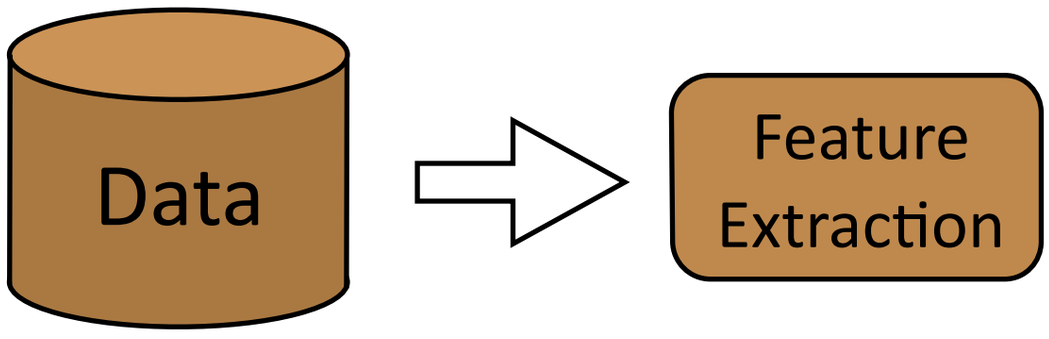

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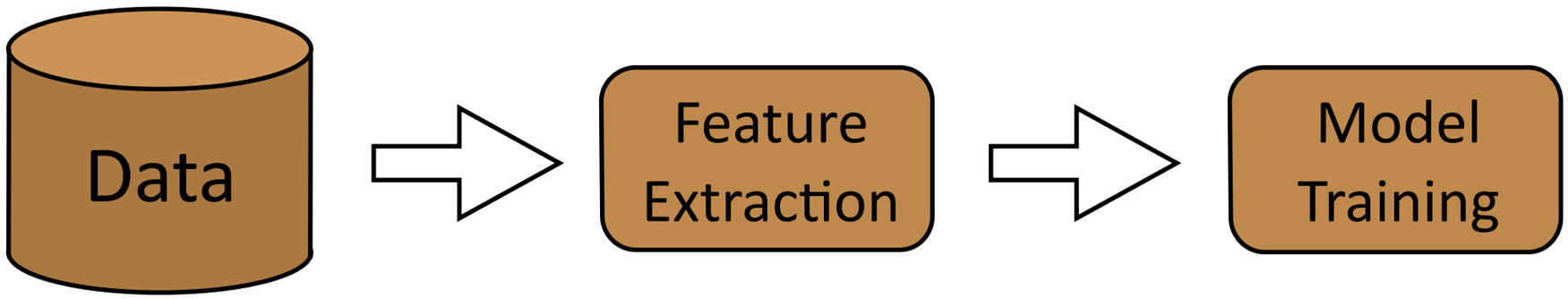

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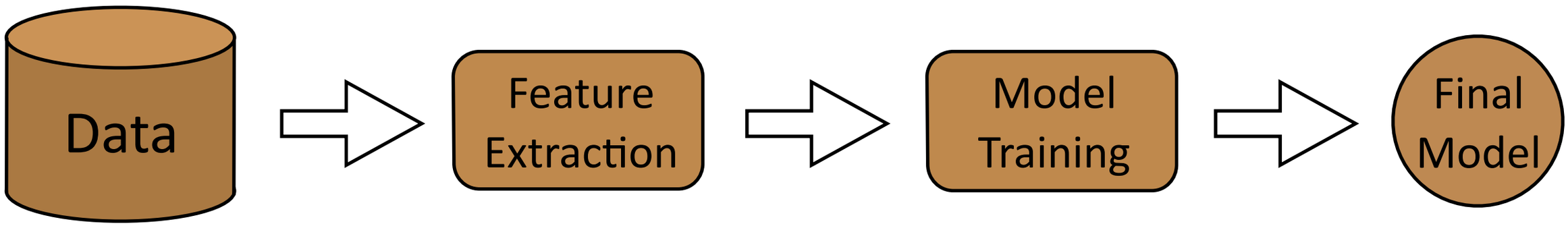

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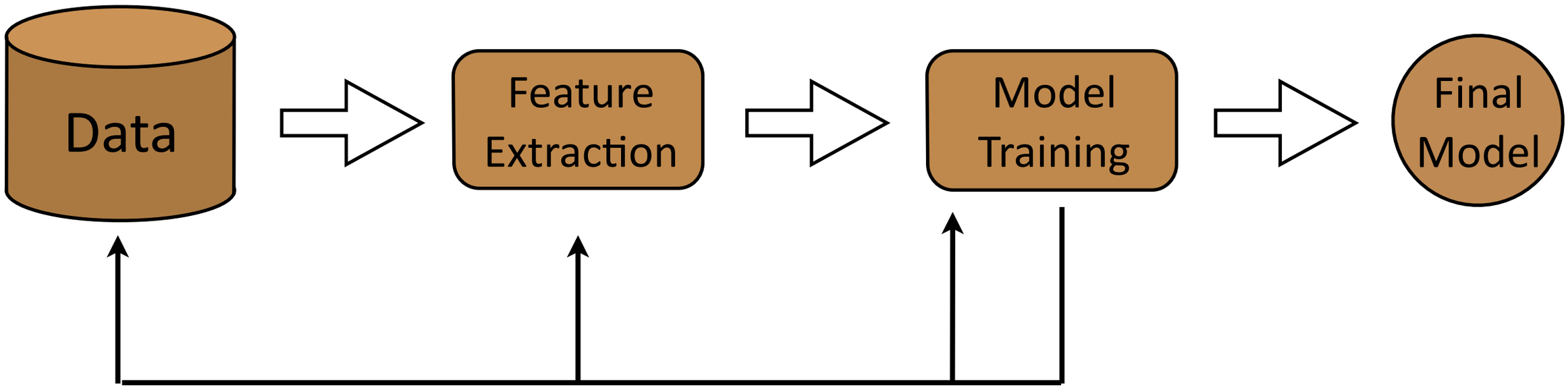

- In practice, model building is an iterative process of continuous refinement

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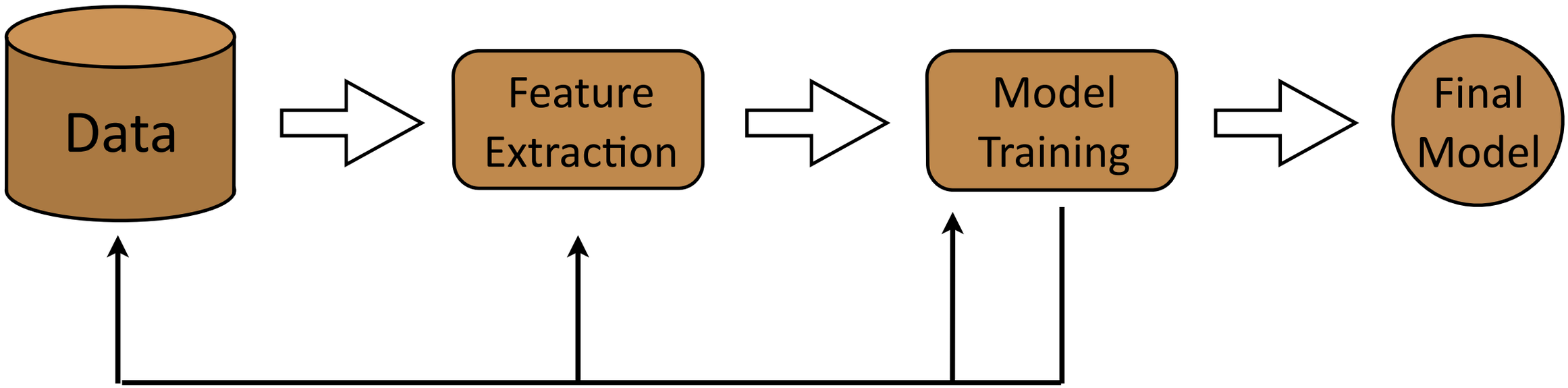

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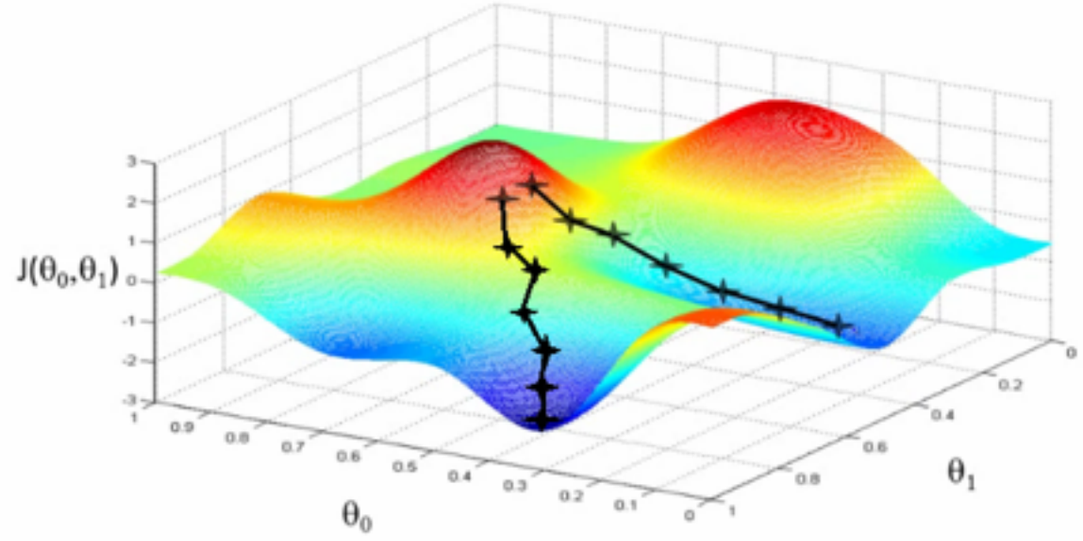
Training A Model

$$w := w - \alpha \nabla Q(w) = w - \alpha \sum_{i=1}^{n} \nabla Q_i(w),$$



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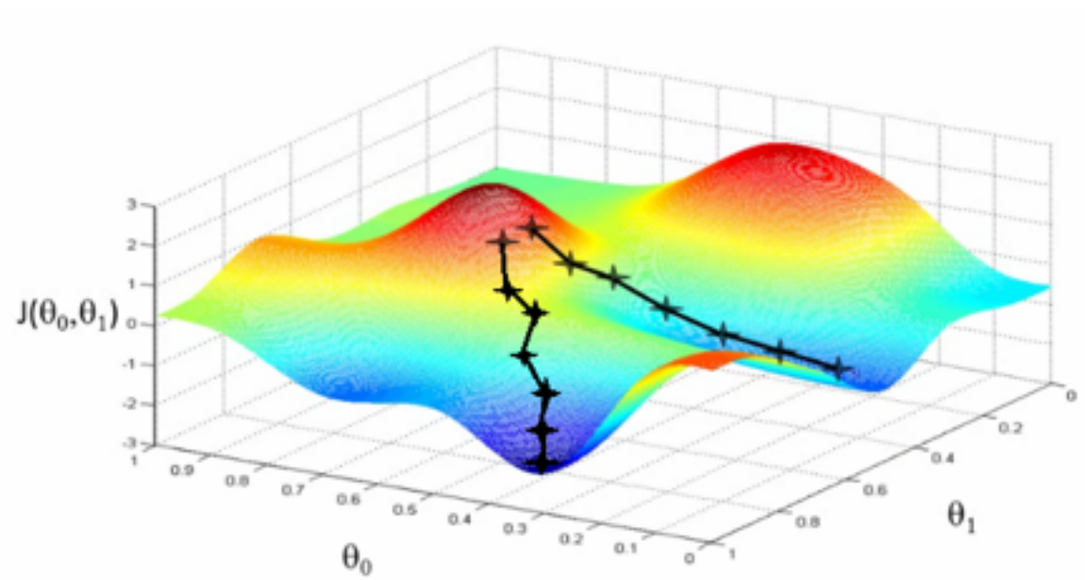

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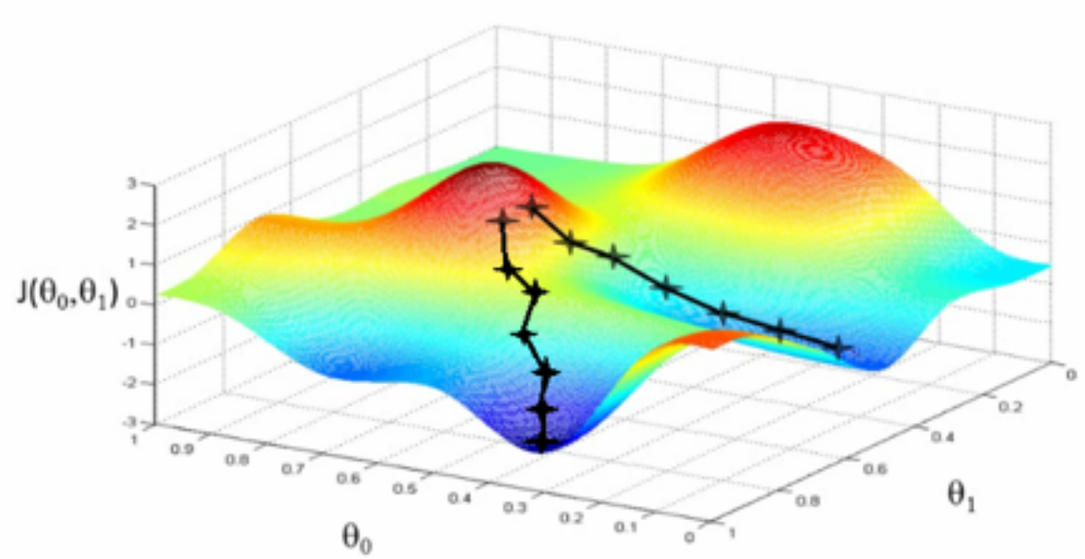

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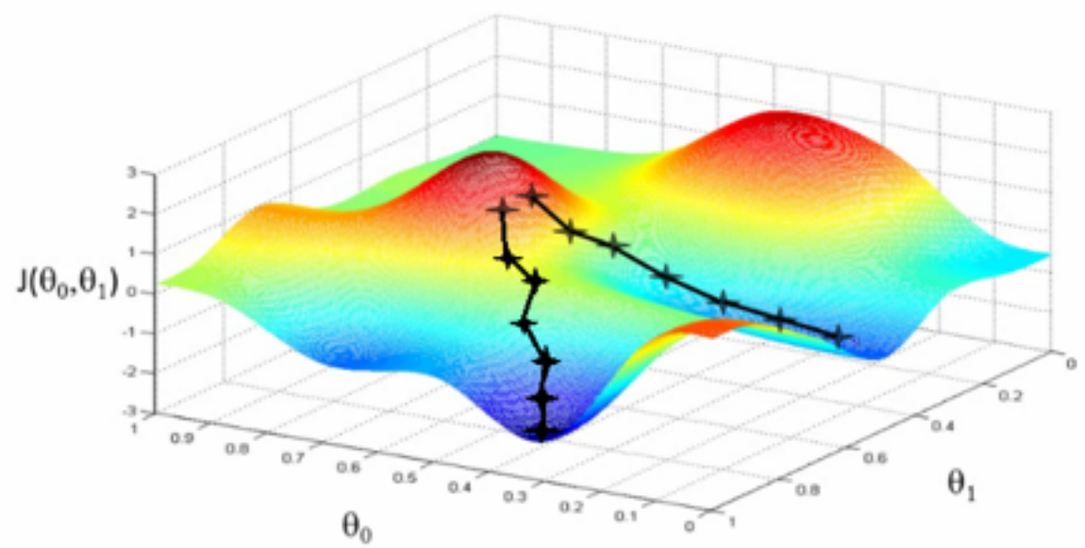

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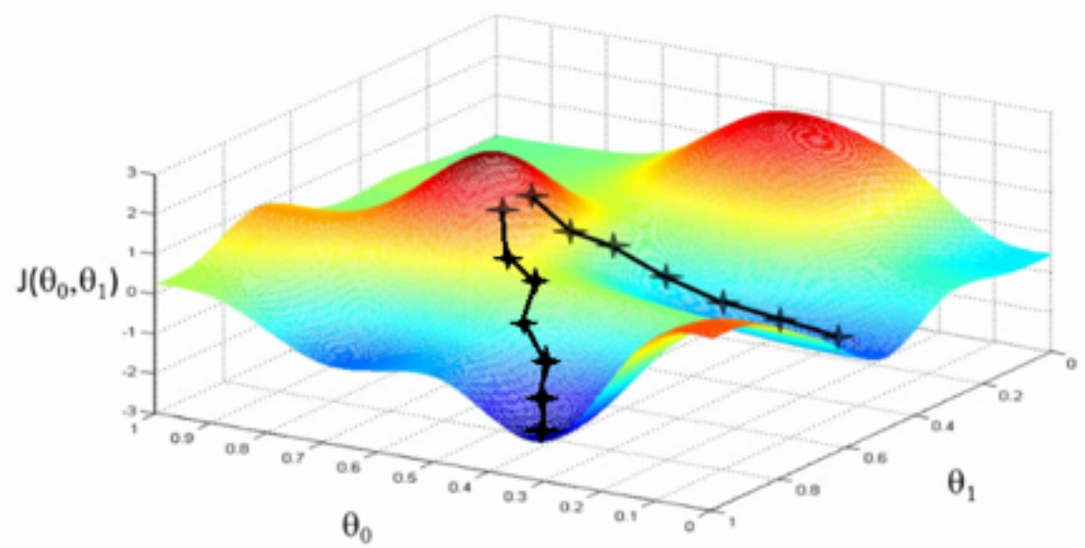

- Requires ***multiple passes***
- Common access pattern
  - Naive Bayes, Trees, etc.
- Minutes to train an SVM on 200GB of data on a 16-node cluster

DATABRICKS

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  - Logistic Regression, SVM, Tree-based, etc.
- Algorithm hyper-parameters
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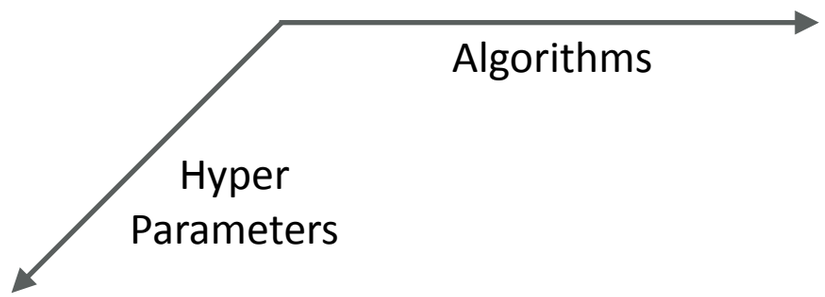

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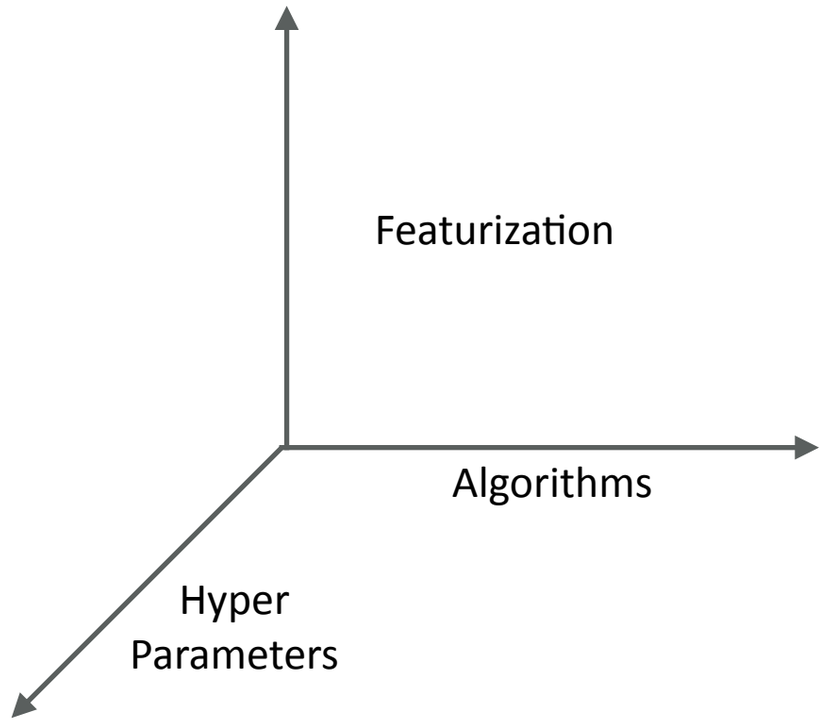

- Featurization
  - Text: n-grams, TF-IDF
  - Images: Gabor filters, random convolutions
  - Random projection? Scaling?

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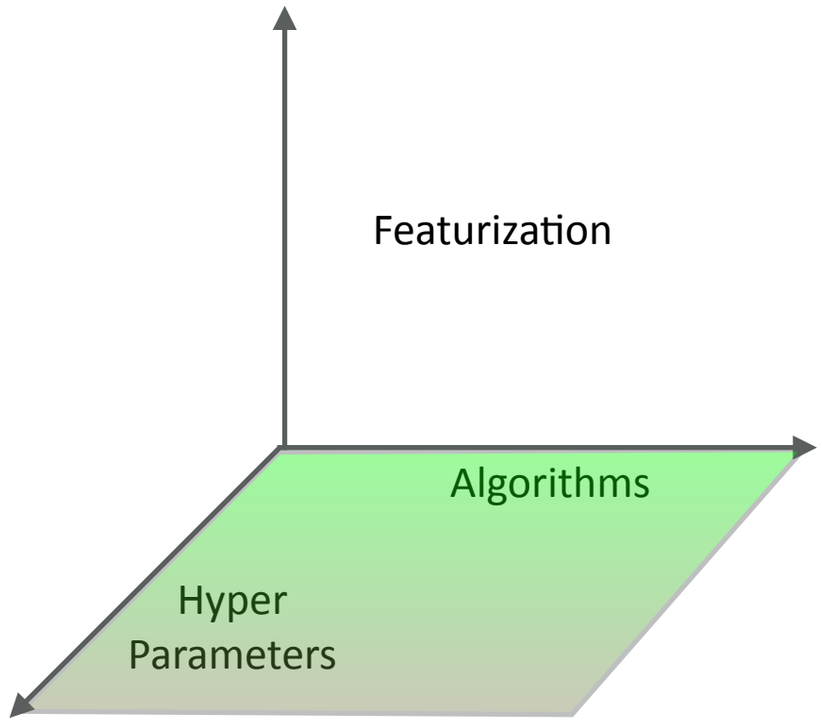

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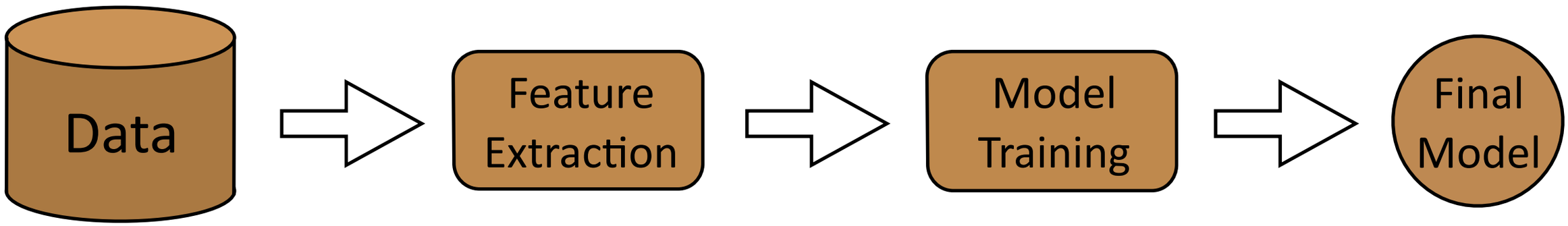

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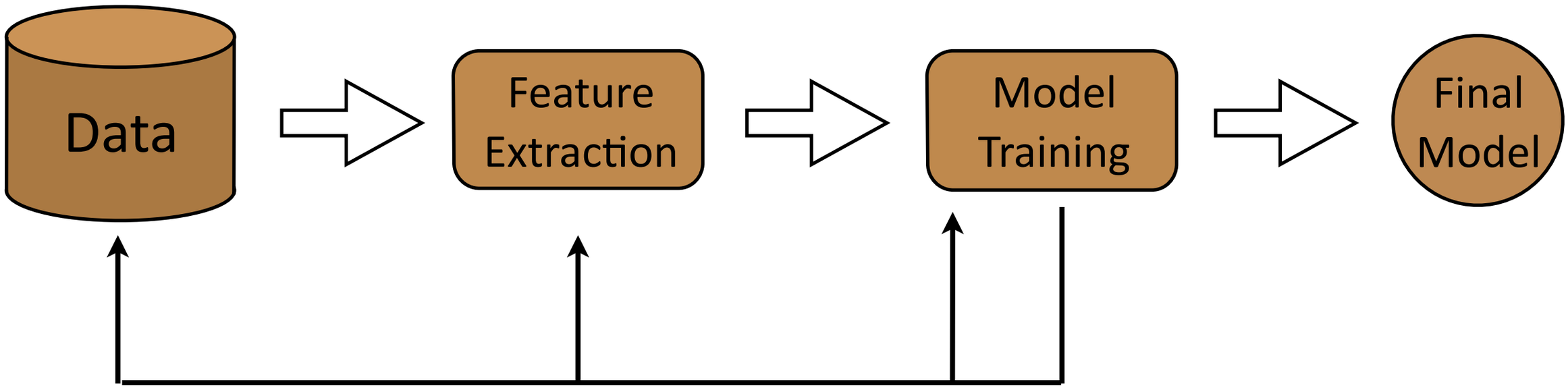

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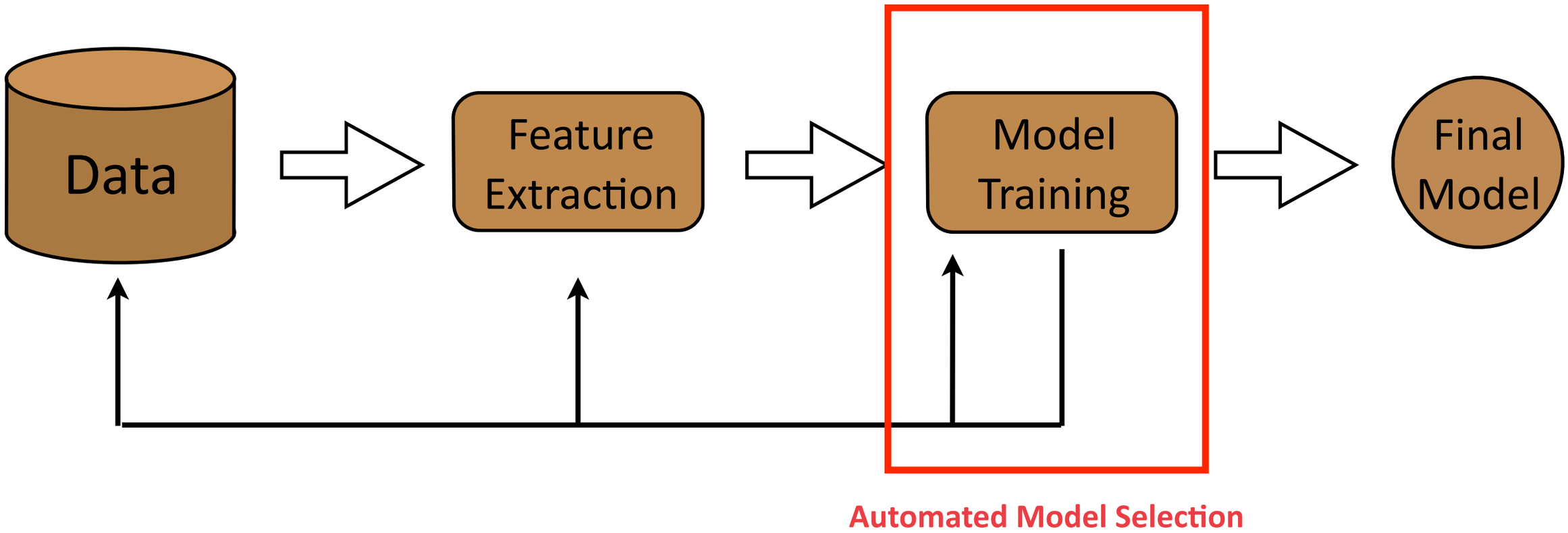

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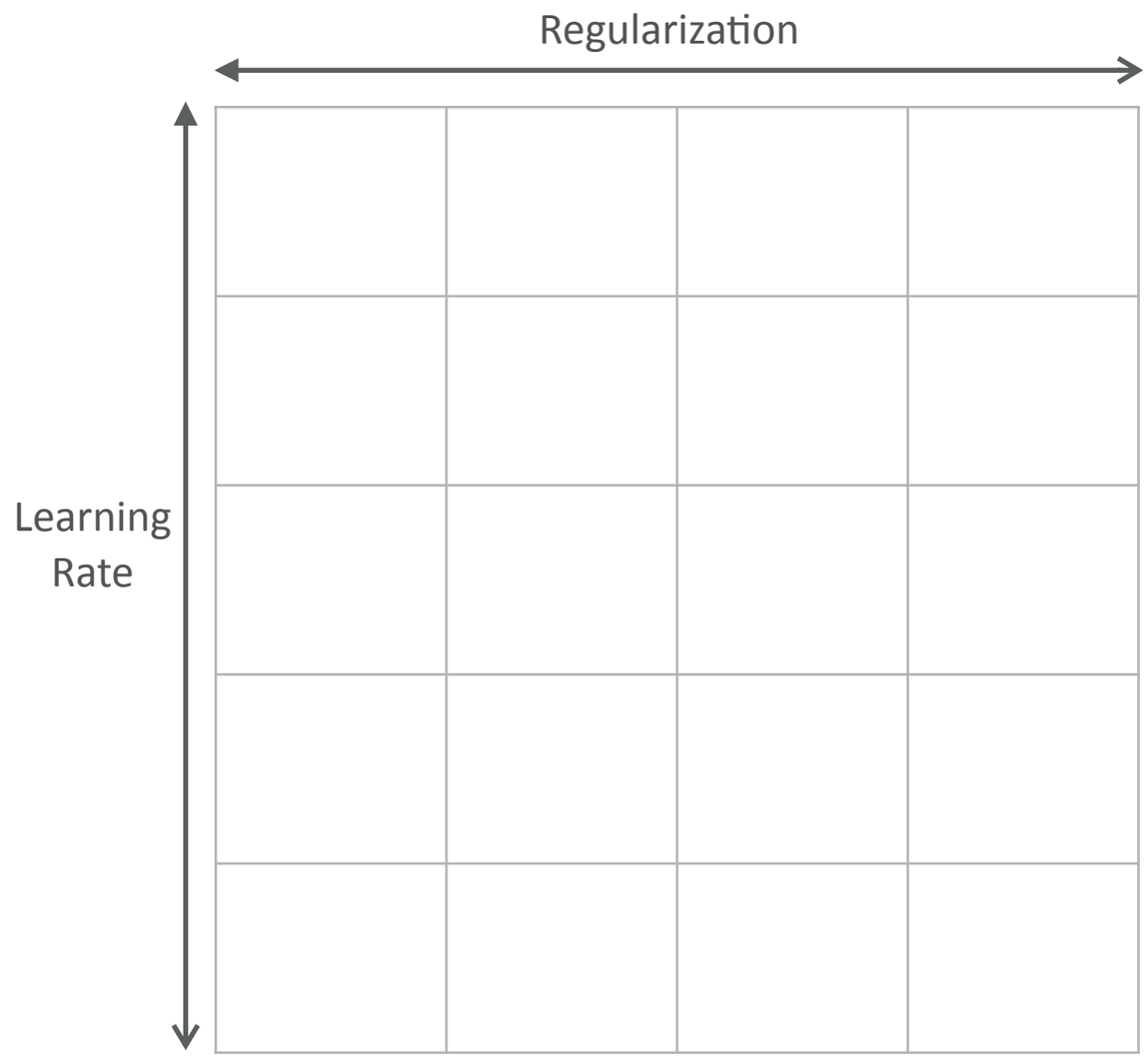
- Start with one aspect of the pipeline - model selection

One Approach



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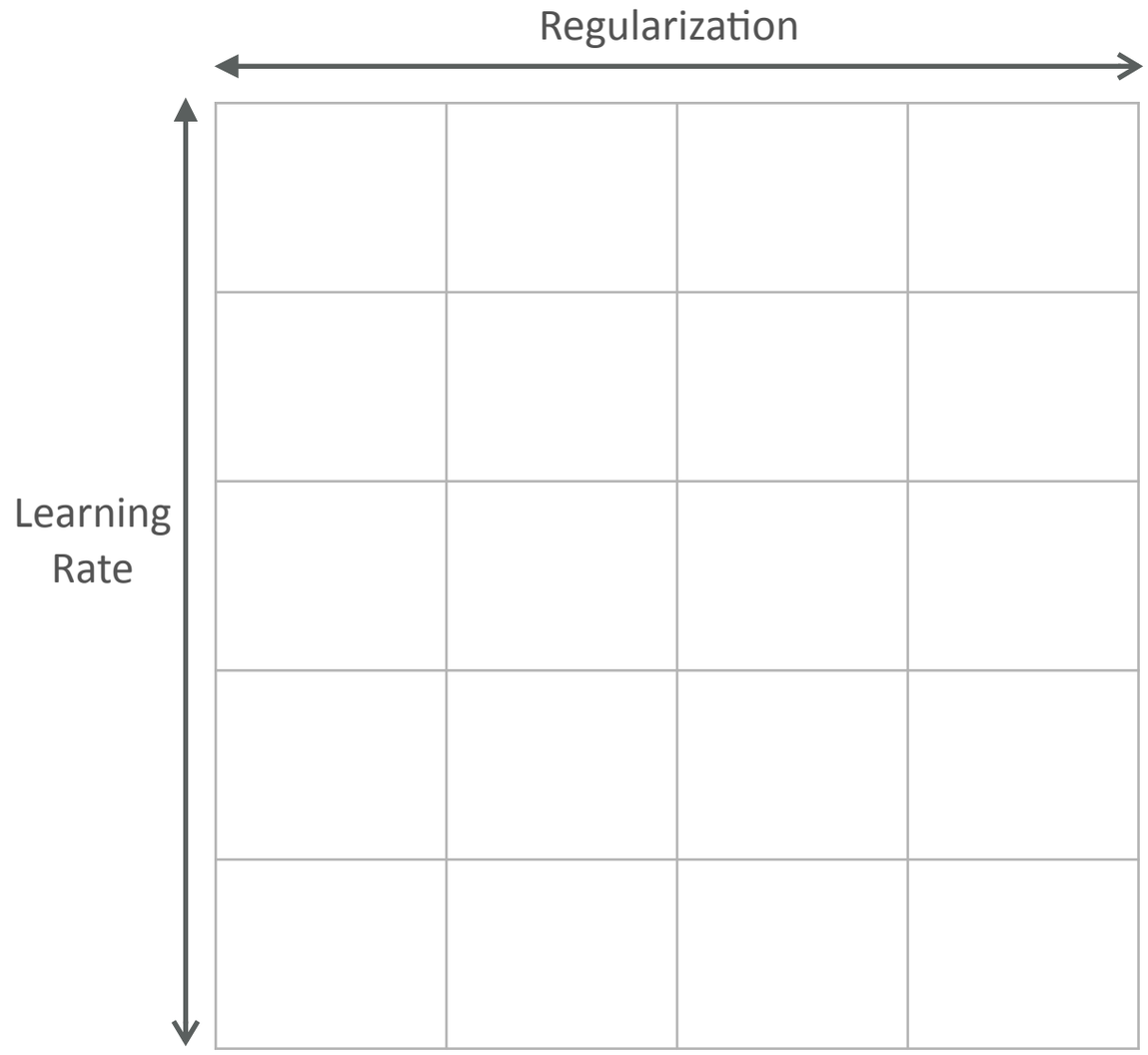
- Try it all!
  - Search over all hyperparameters, algorithms, features, etc.



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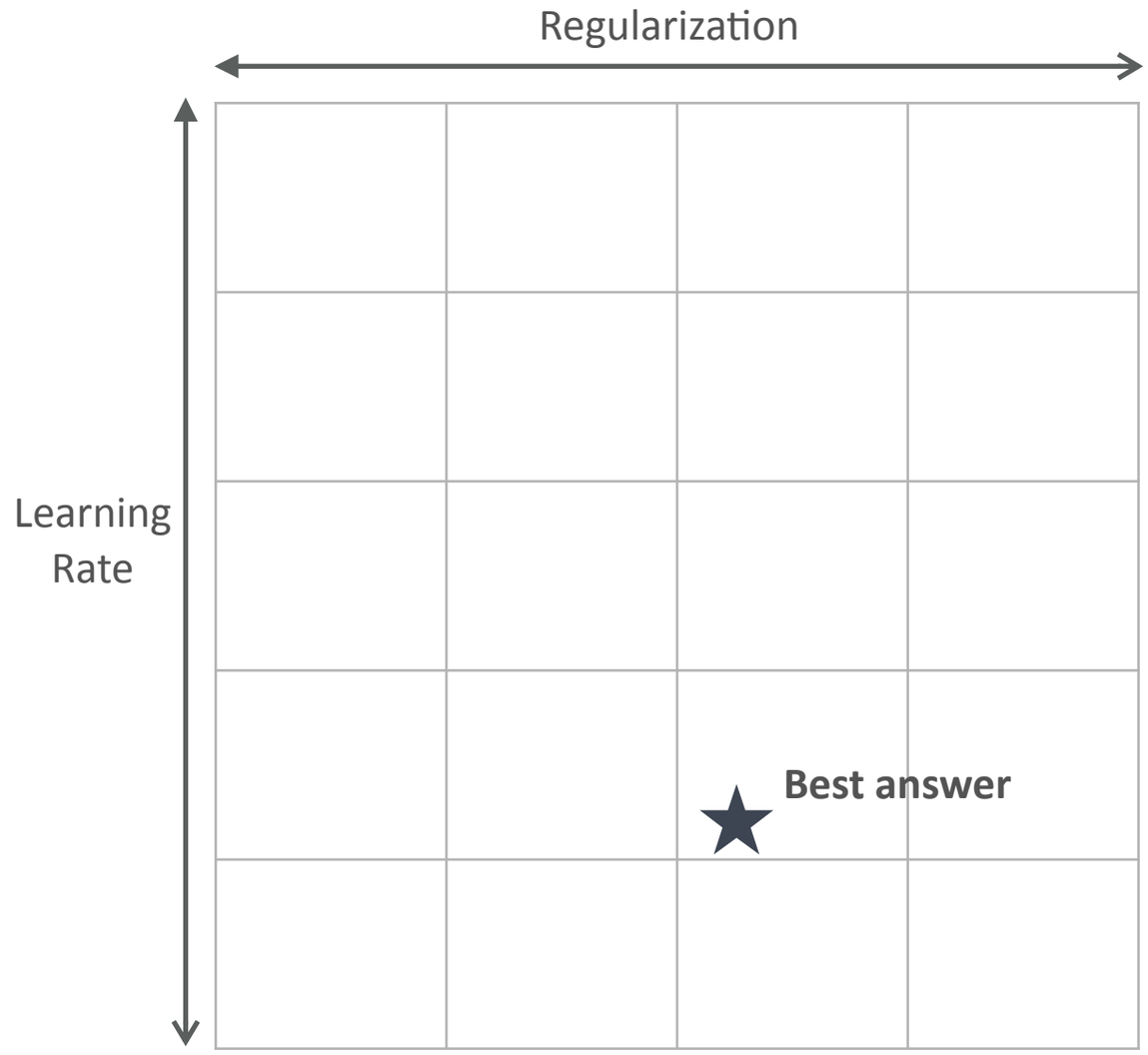

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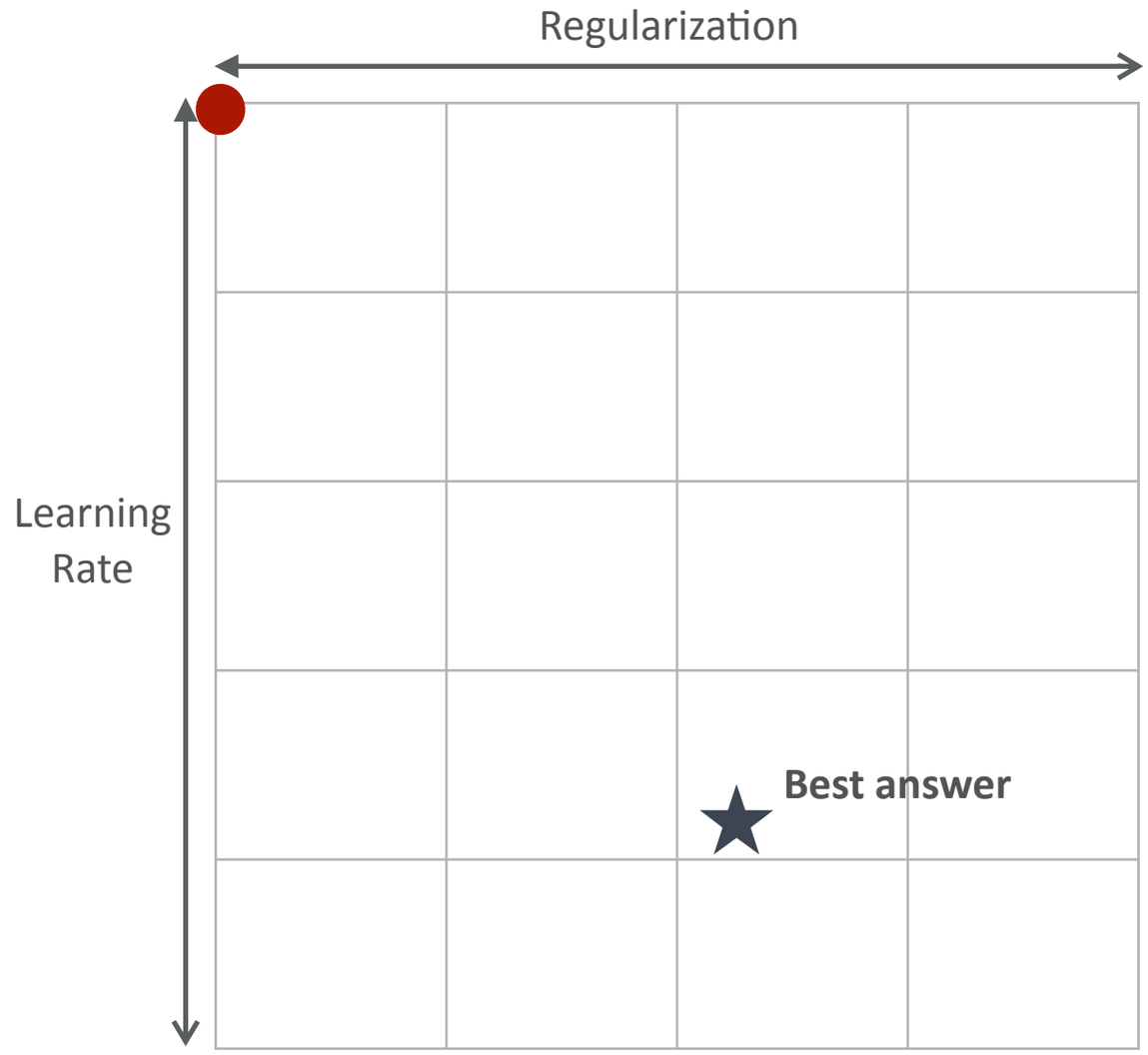

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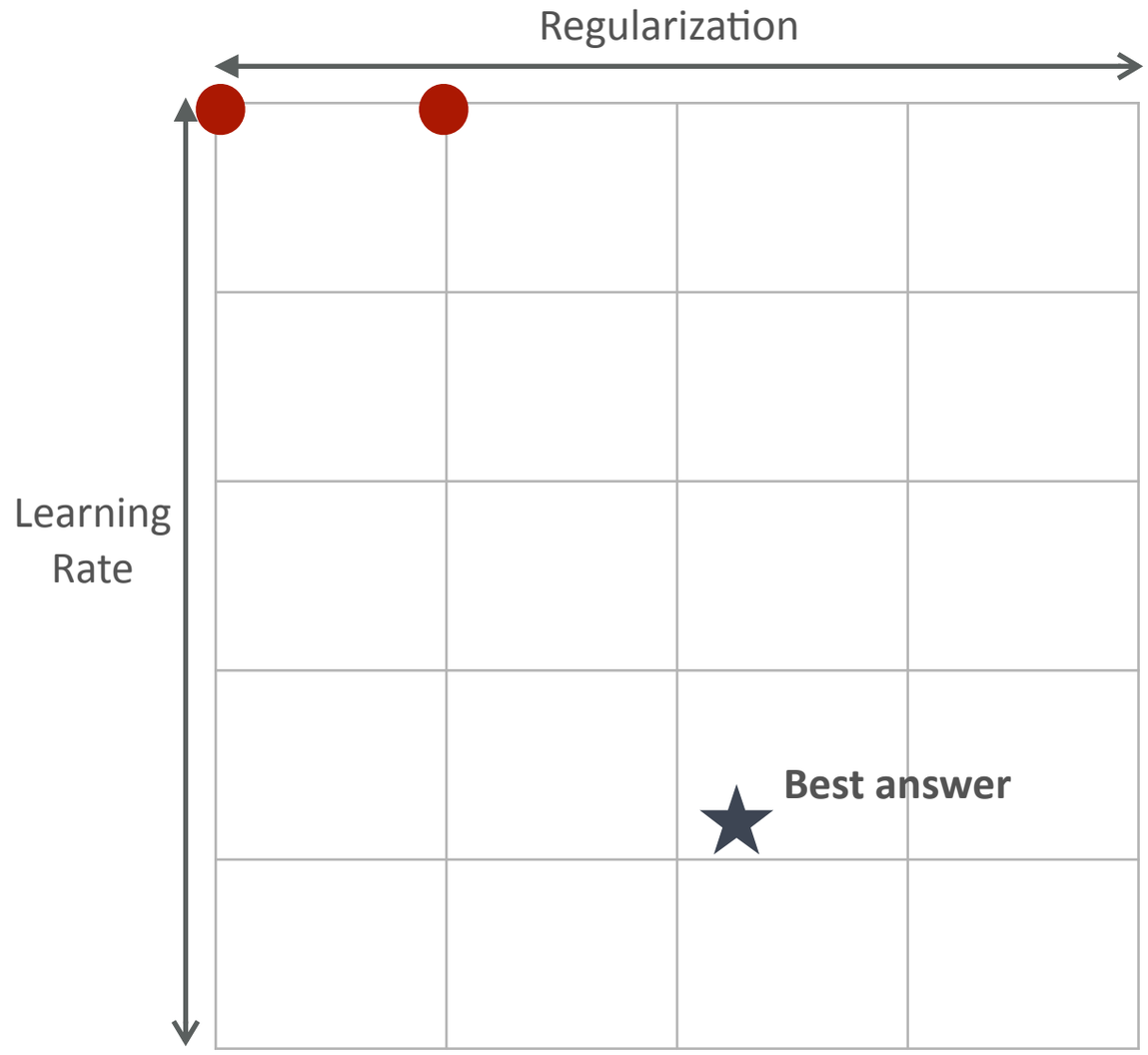

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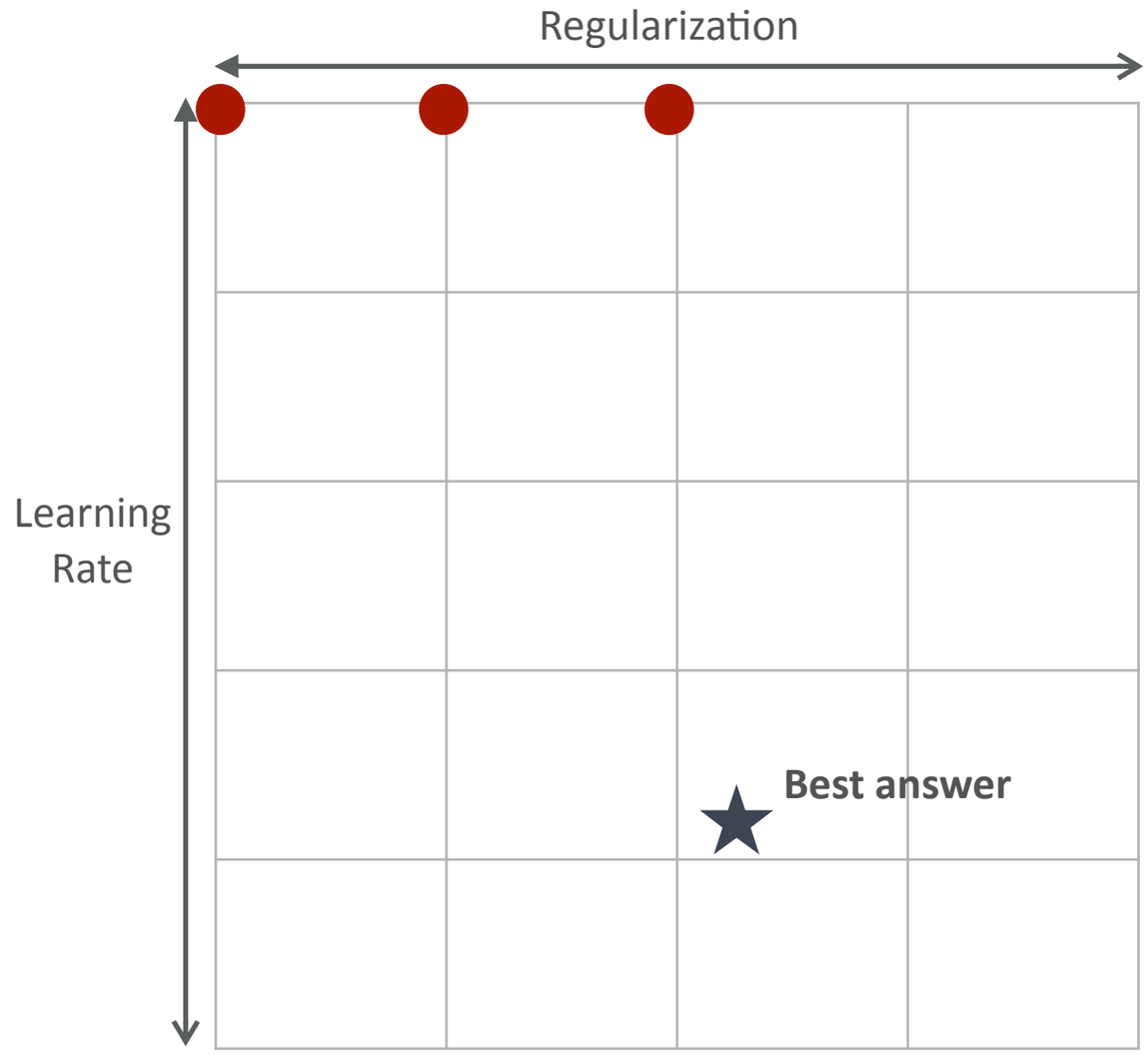

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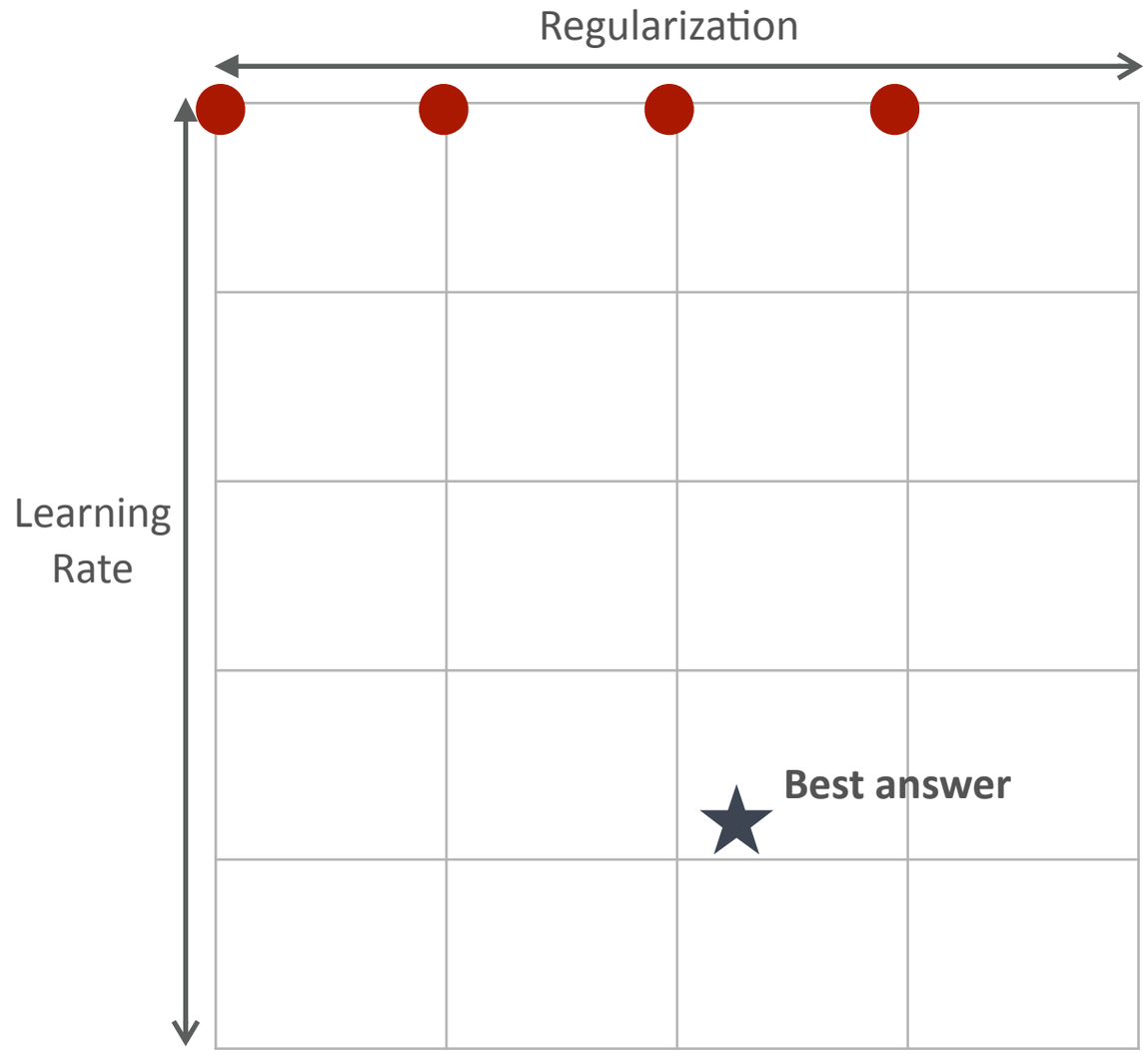

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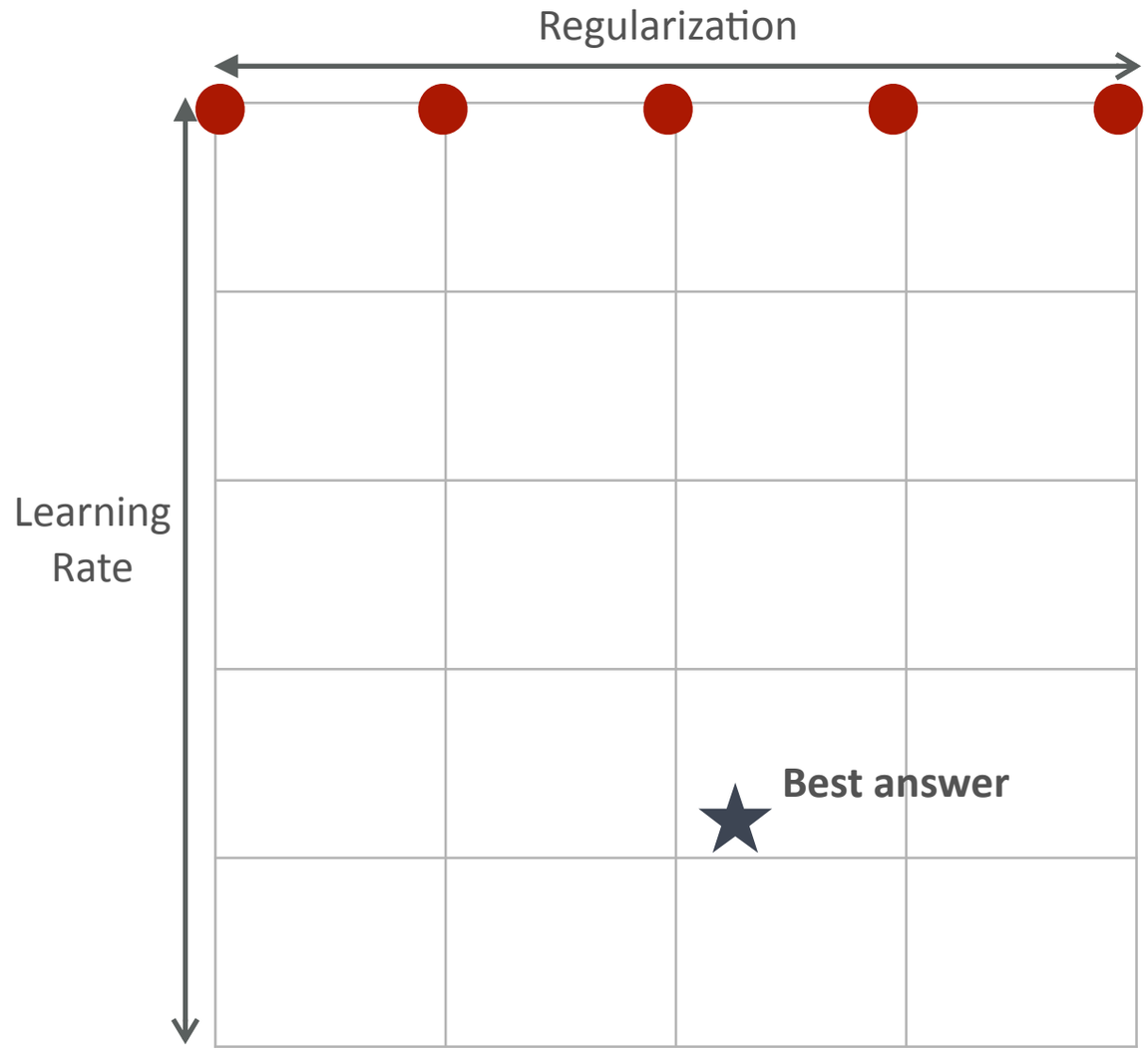

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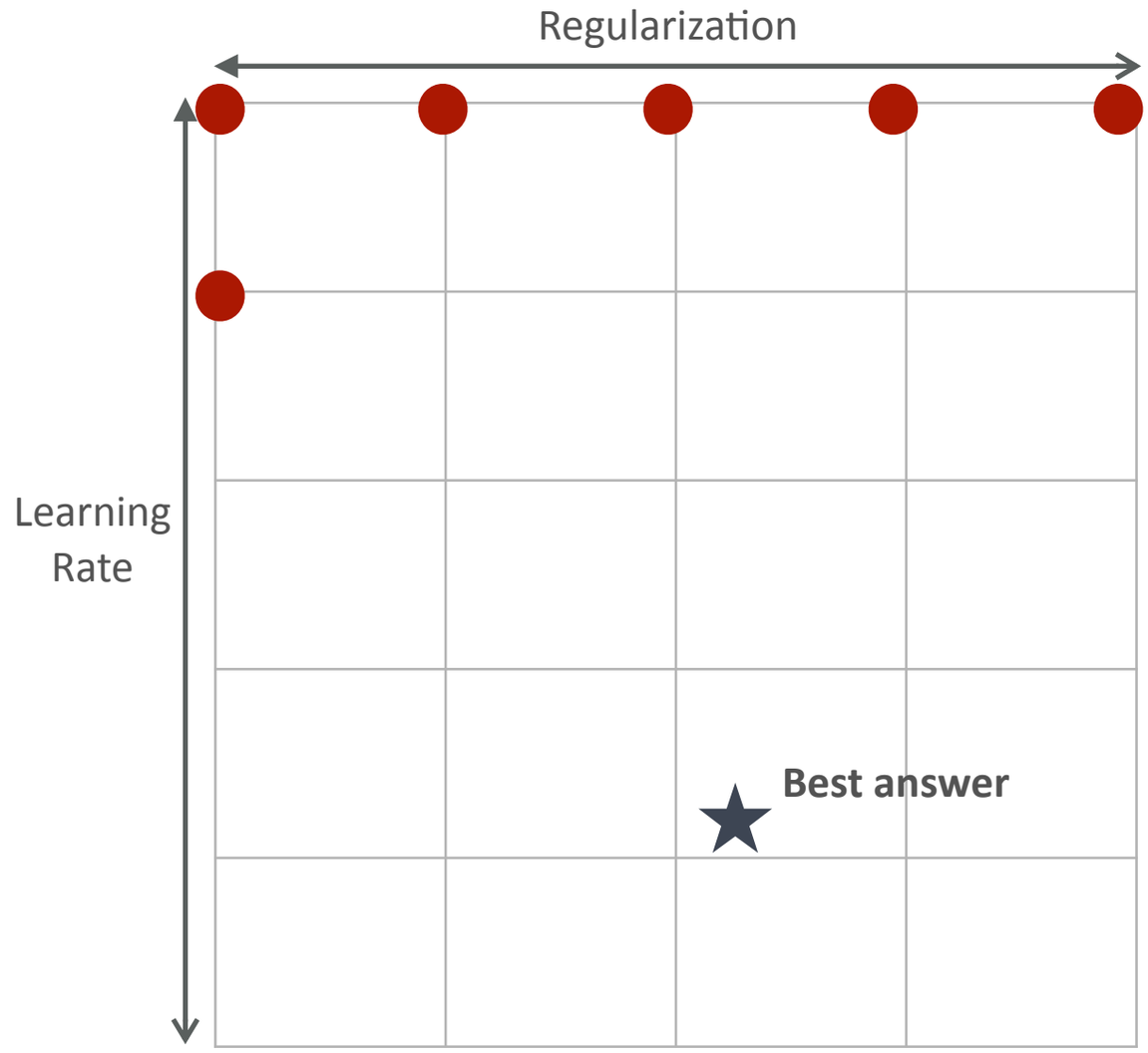

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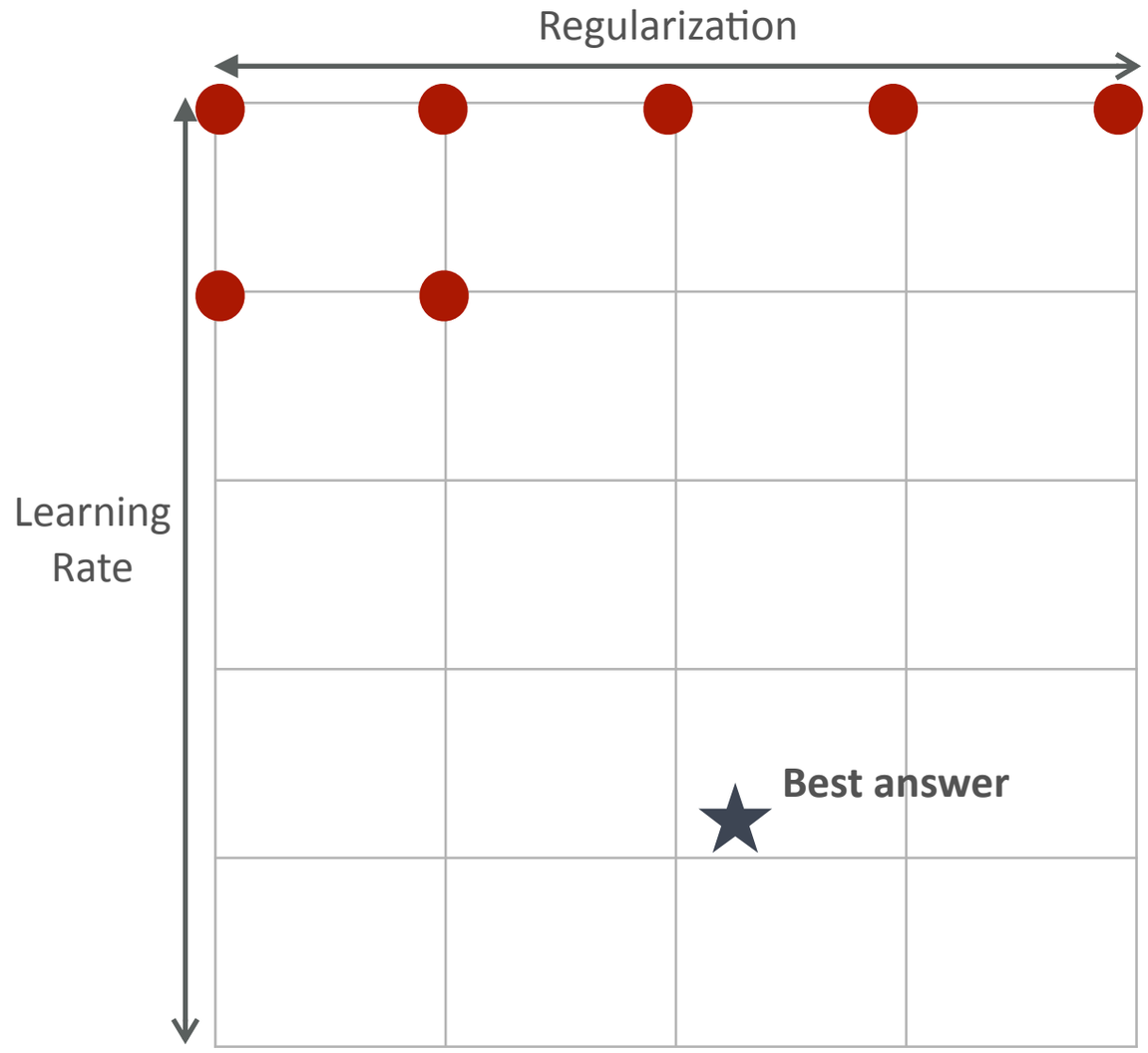

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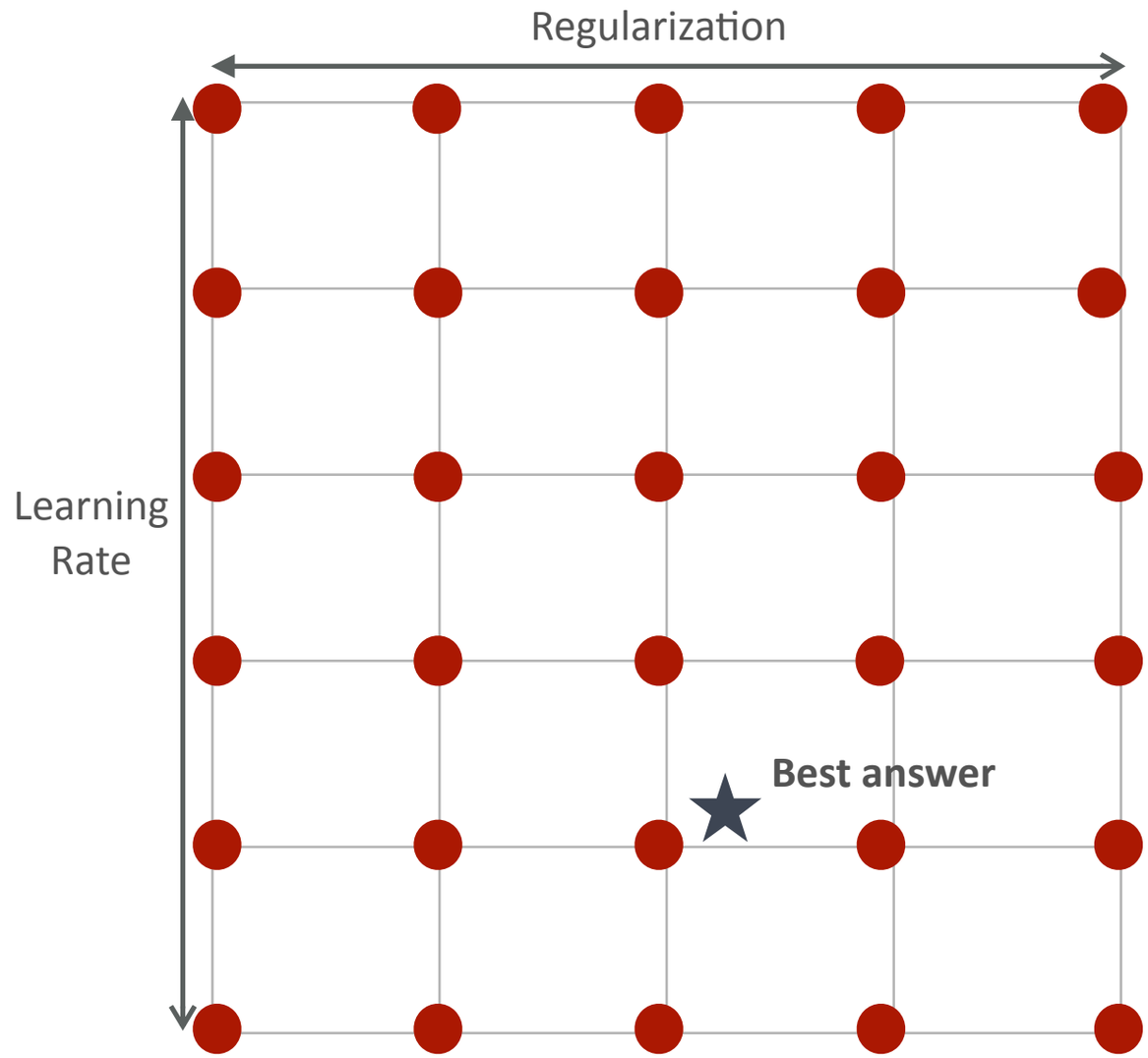
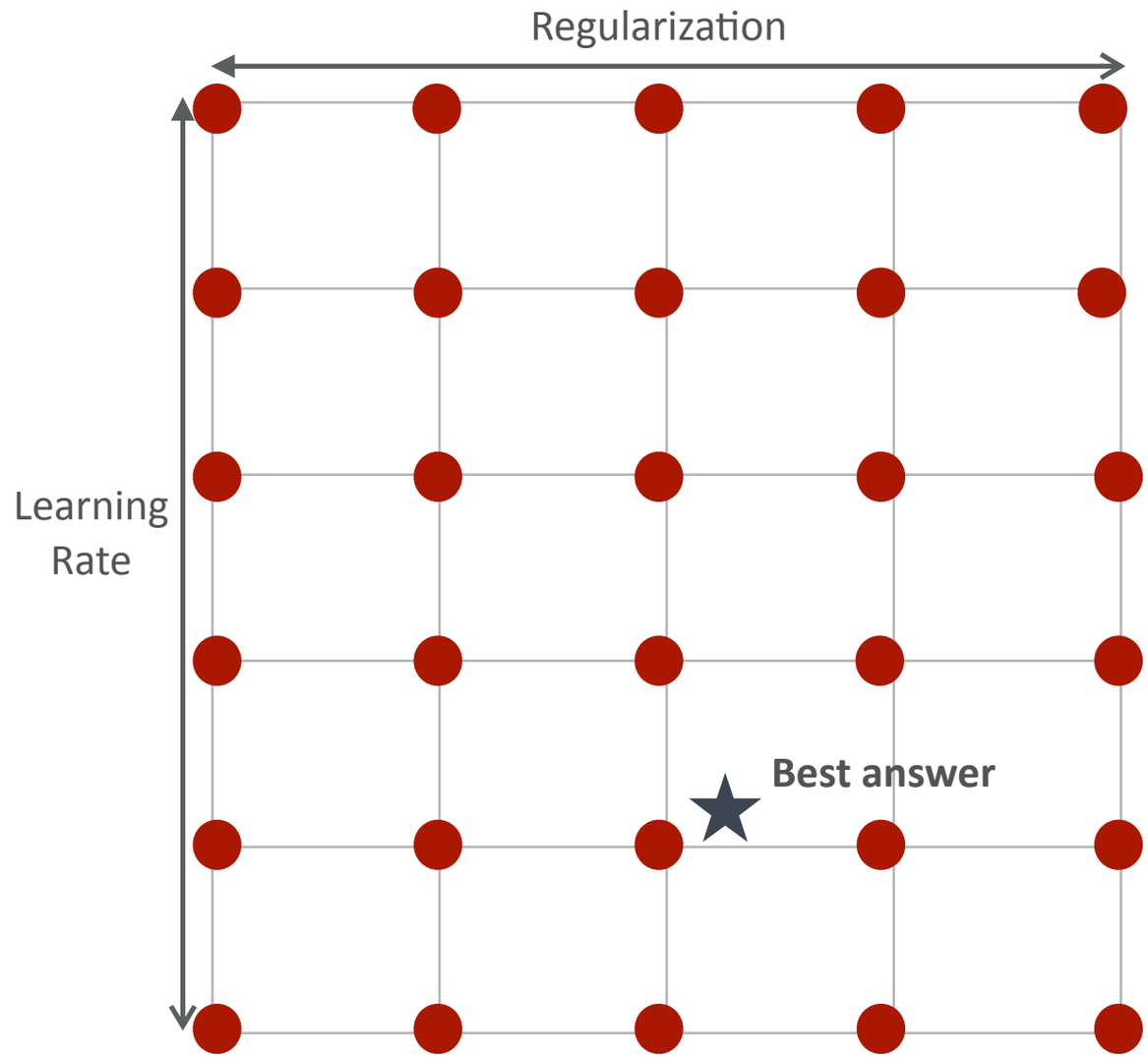


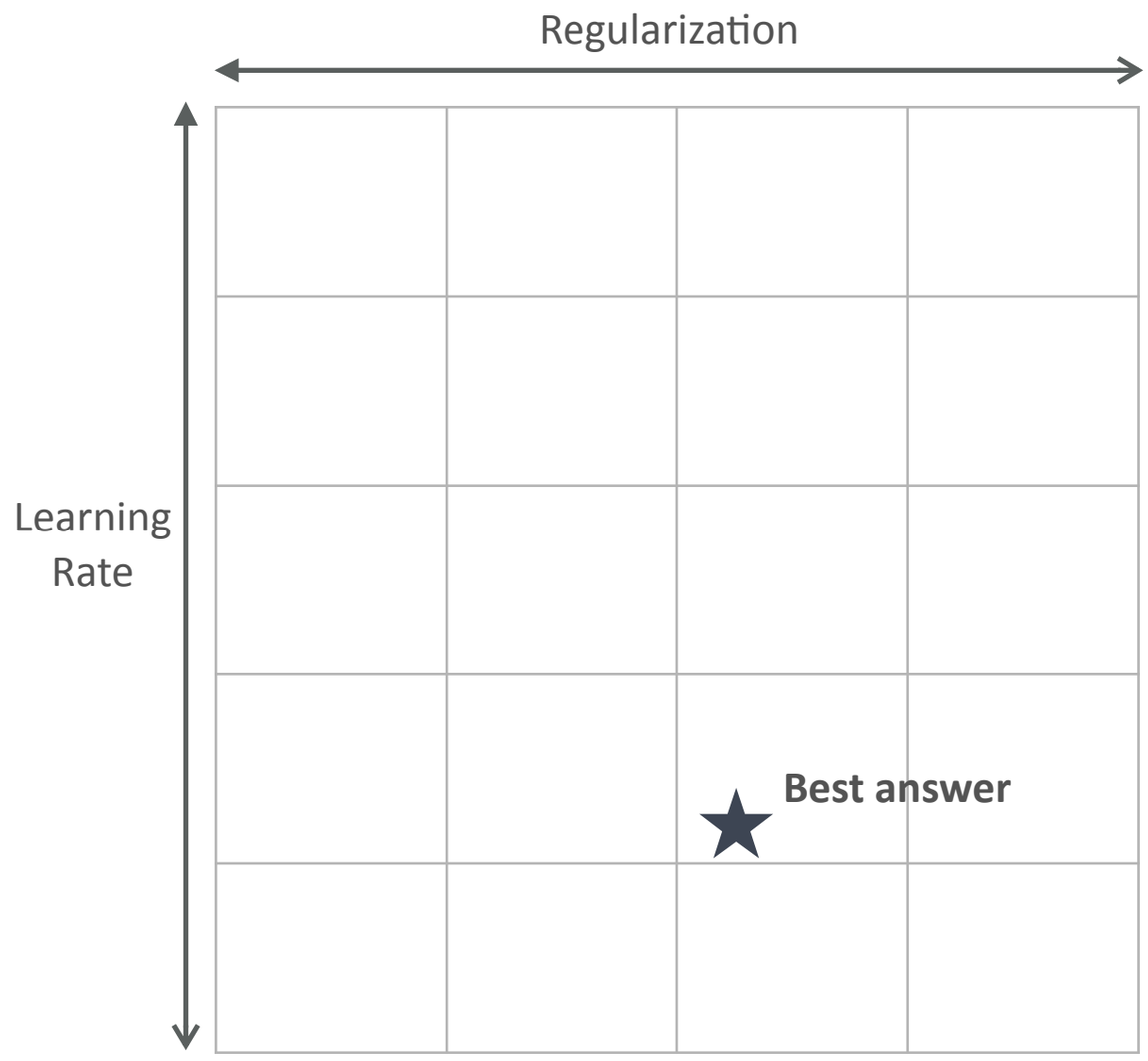
One Approach

- Try it all!
  - Search over all hyperparameters, algorithms, features, etc.
- Drawbacks
  - Expensive to compute models
  - Hyperparameter space is large
- Some version of this still often done in practice!



A Better Approach

- Better resource utilization
  - through batching
- Algorithmic Speedups
  - via early stopping
- Improved Search
  - e.g., via randomization



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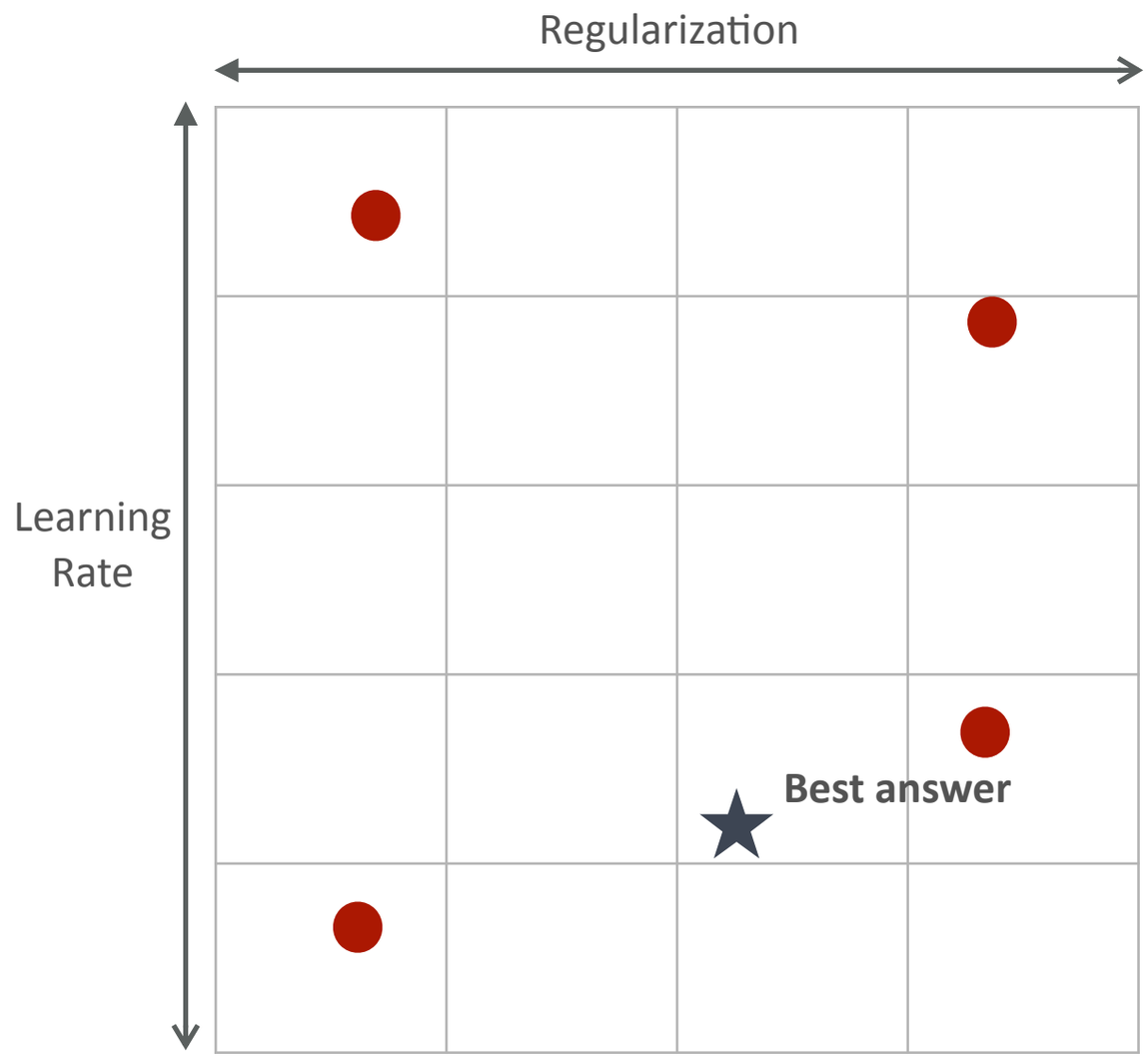

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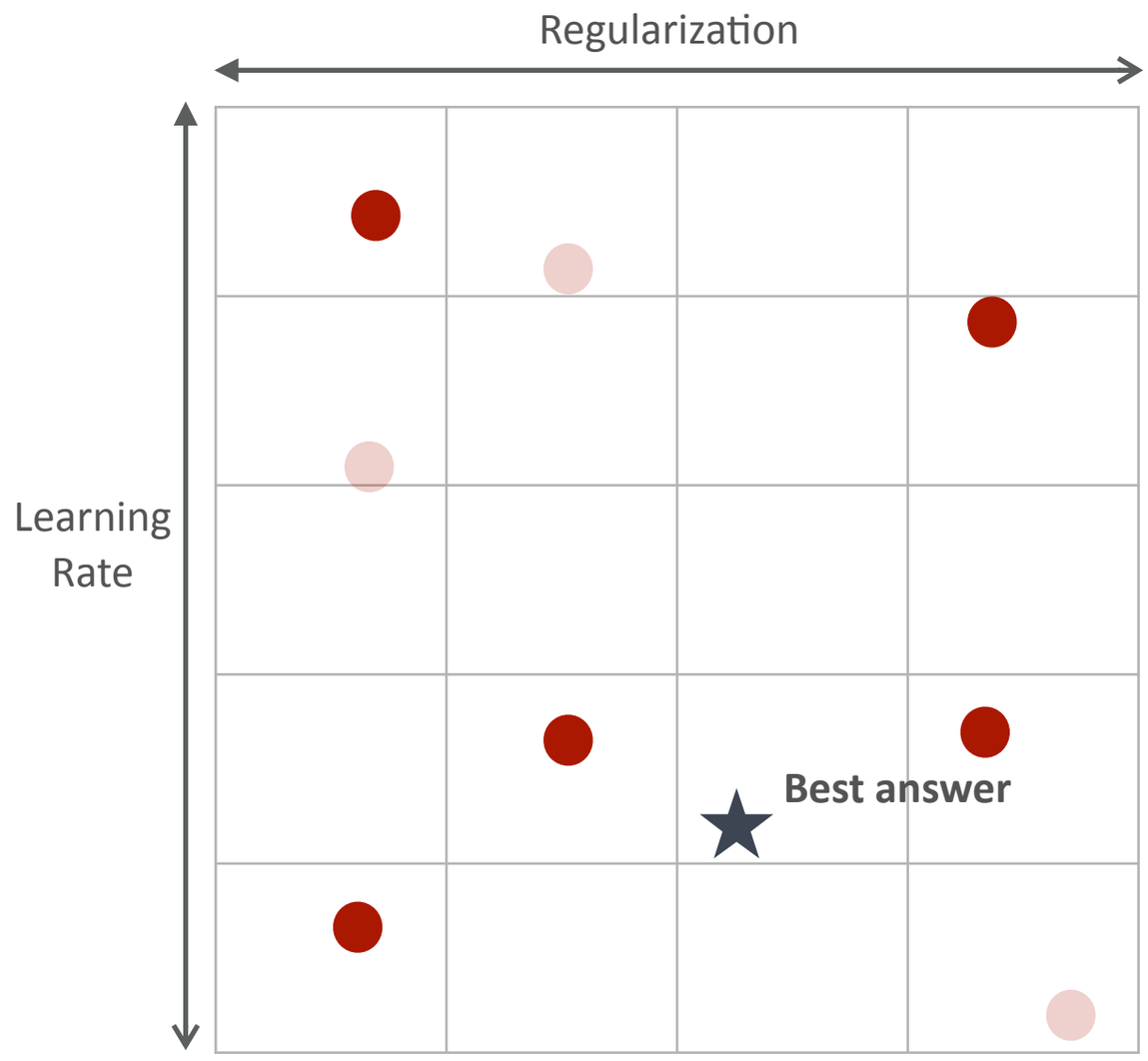

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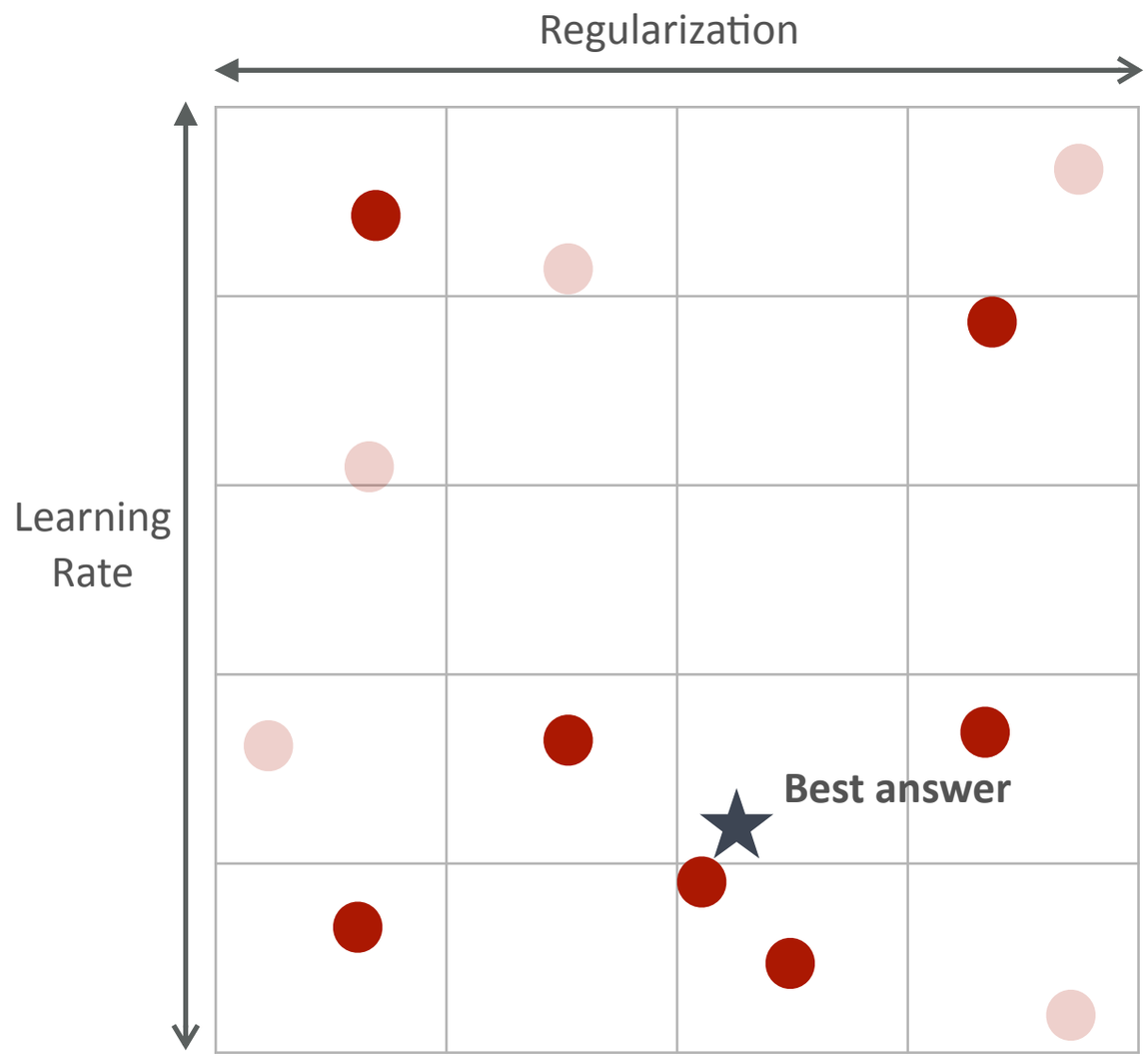

A Tale Of 3 Optimizations

Better Resource Utilization

Algorithmic Speedups

Improved Search

DATABRICKS

Better Resource Utilization

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- ✦ Modern memory slower than processors
- ✦ Can read: 0.6b doubles/sec/core (4.8 GB/s)
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DATABRICKS

What Does This Mean For Modeling?

A	B	C
1	a	Dog
1	b	Cat
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2	d	Cat
3	e	Dog
3	f	Horse
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- Typical model update requires 2-4 flops/double
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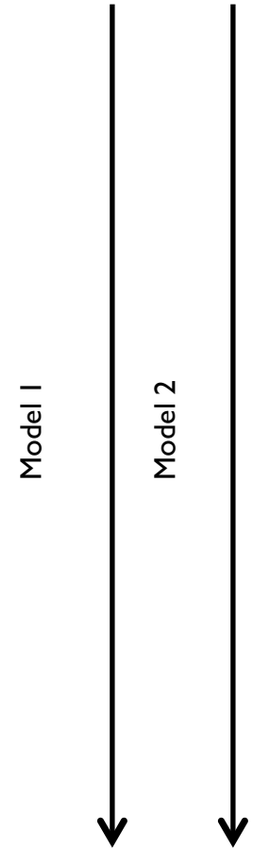

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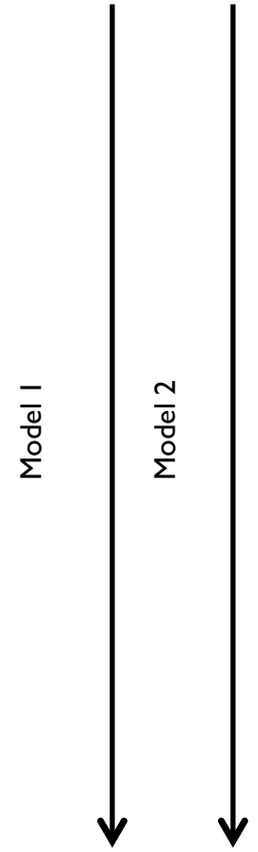
- **Train multiple models simultaneously**



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What Do We See In Spark?

- 2x and 5x increase in models trained/sec with batching
- Overhead from virtualization, network, etc.

Batch Size \ D	100	500	1000	10000
1	1.00	1.00	1.00	1.00
2	1.91	1.50	1.51	1.38
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10	5.31	3.40	2.37	1.14

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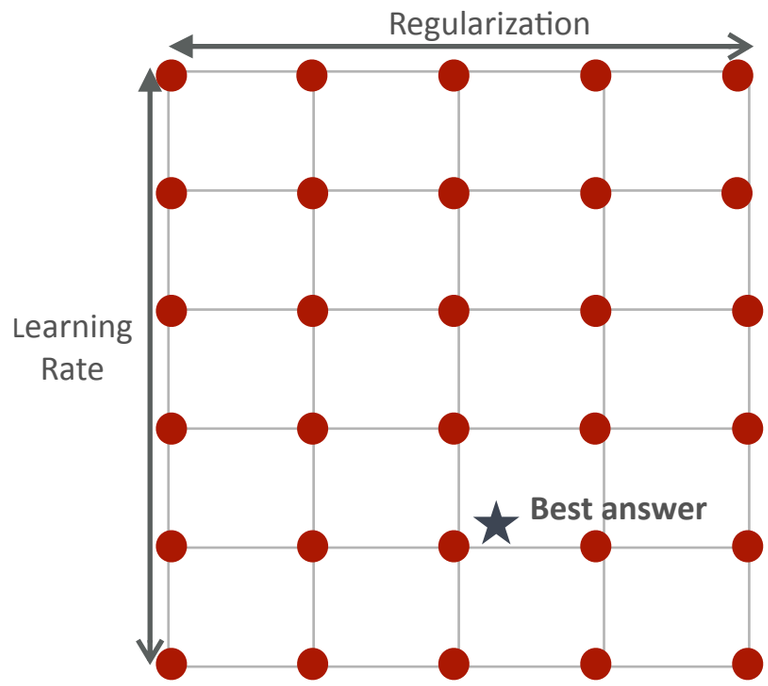

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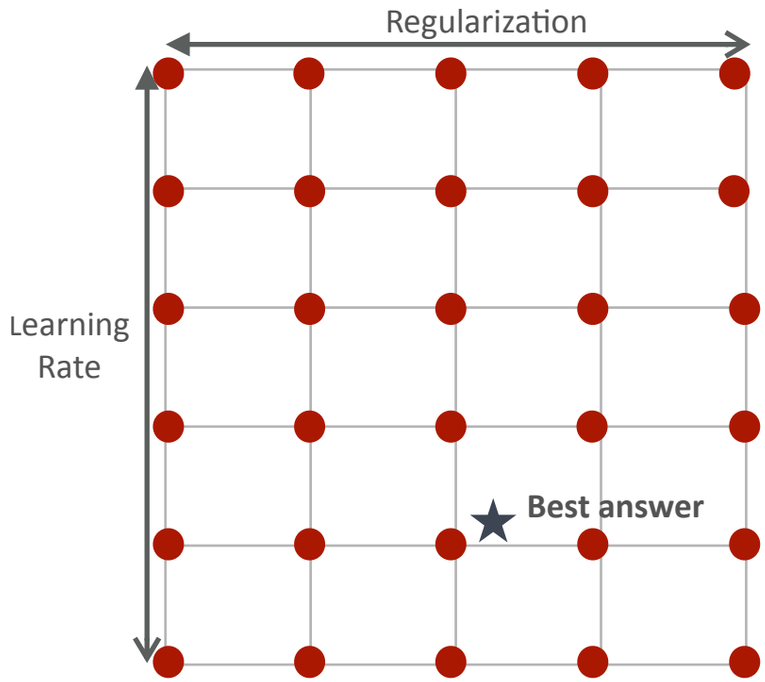

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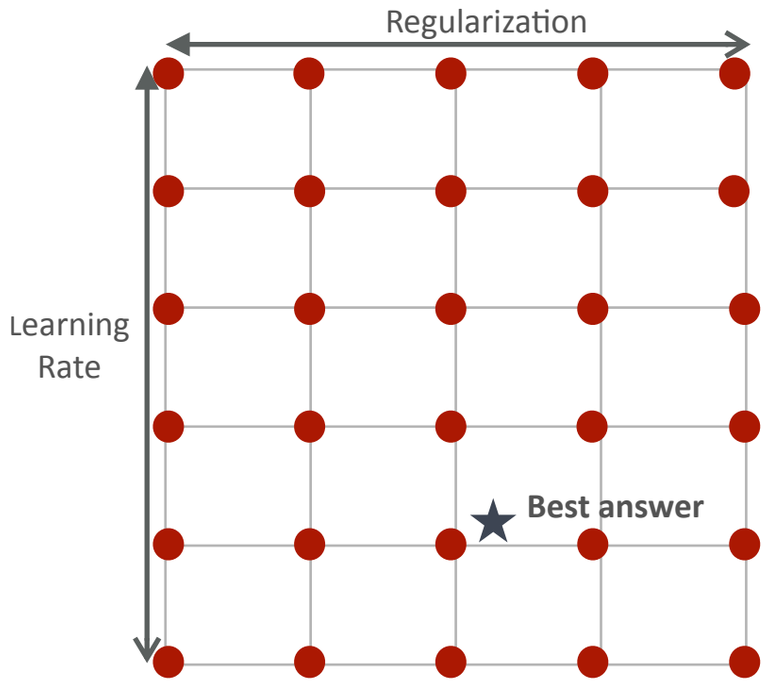

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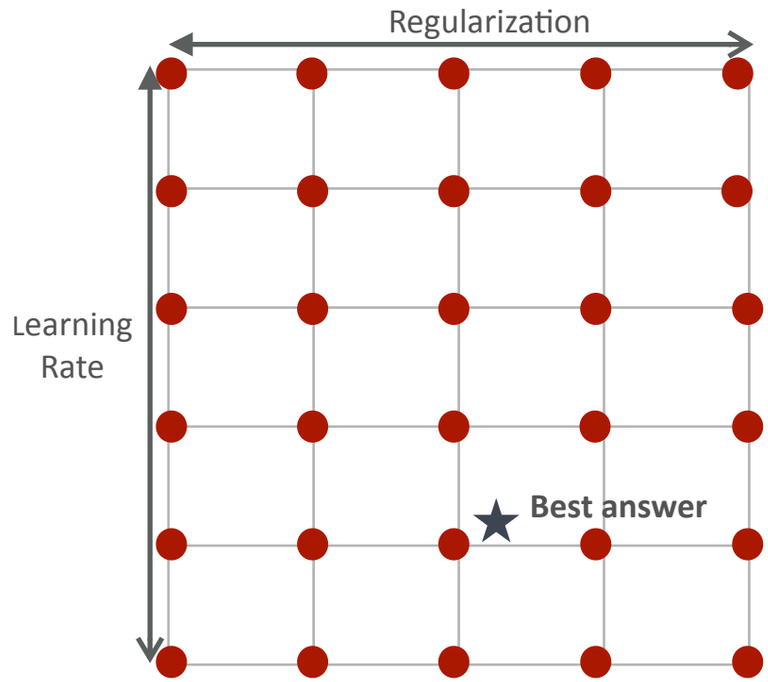

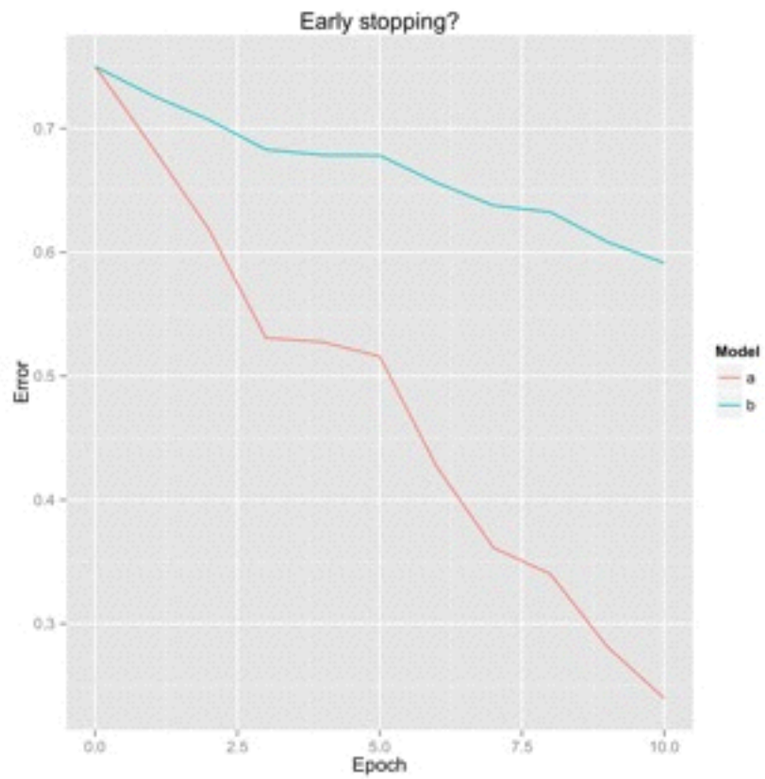

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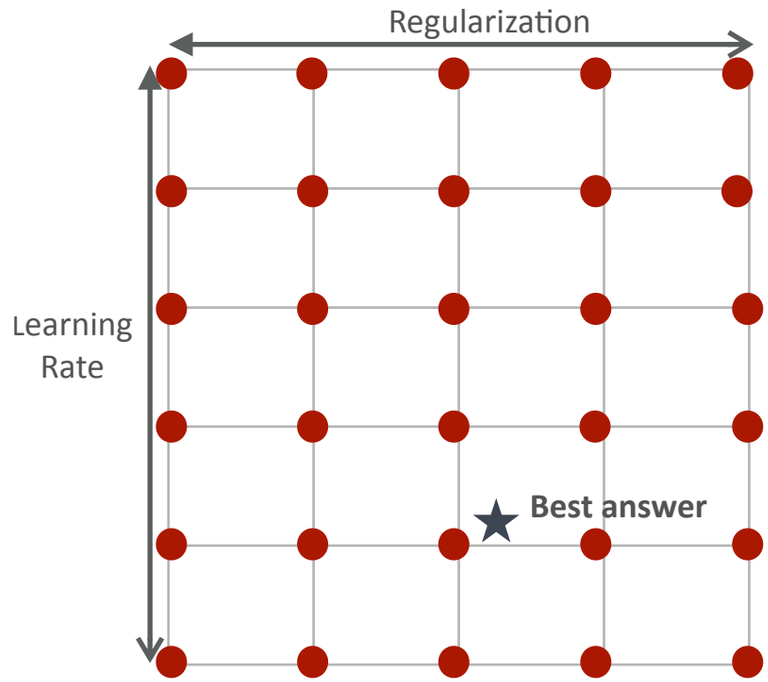

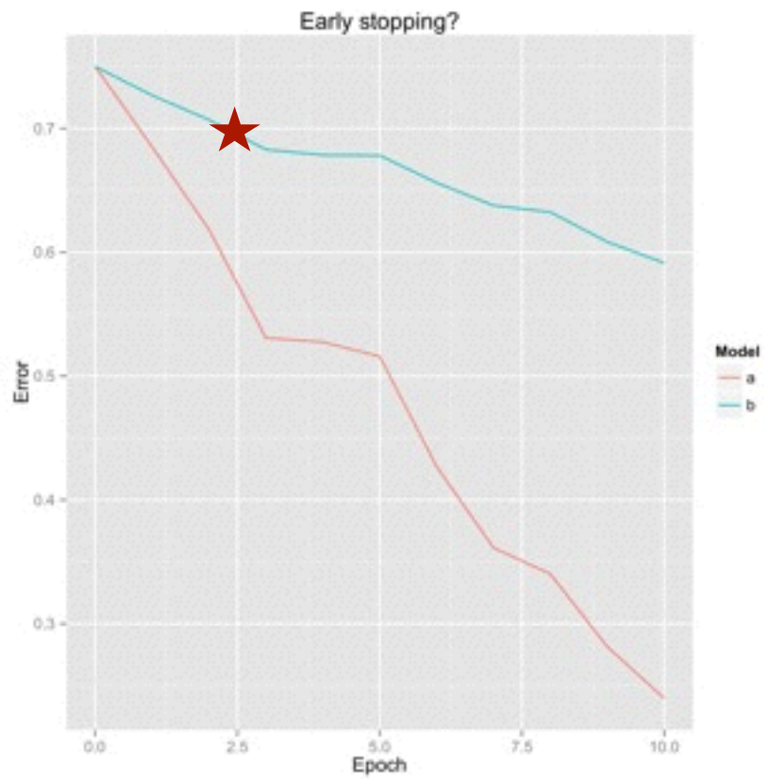

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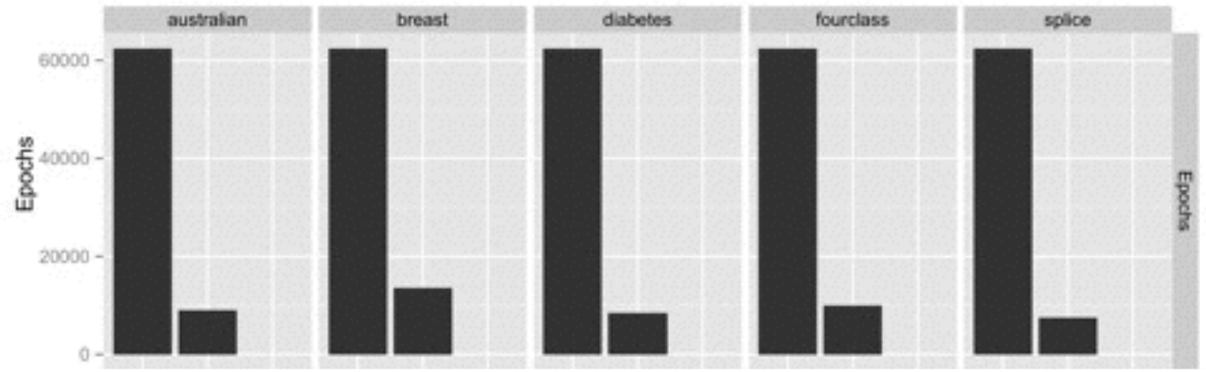

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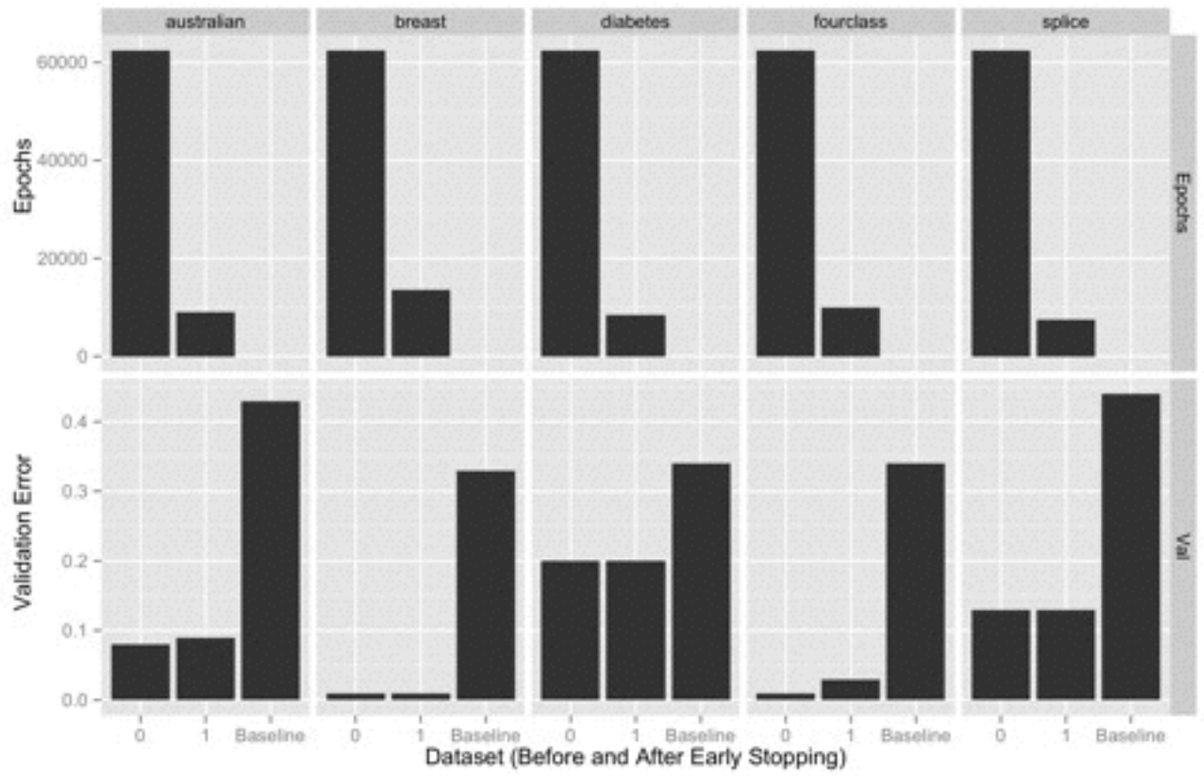

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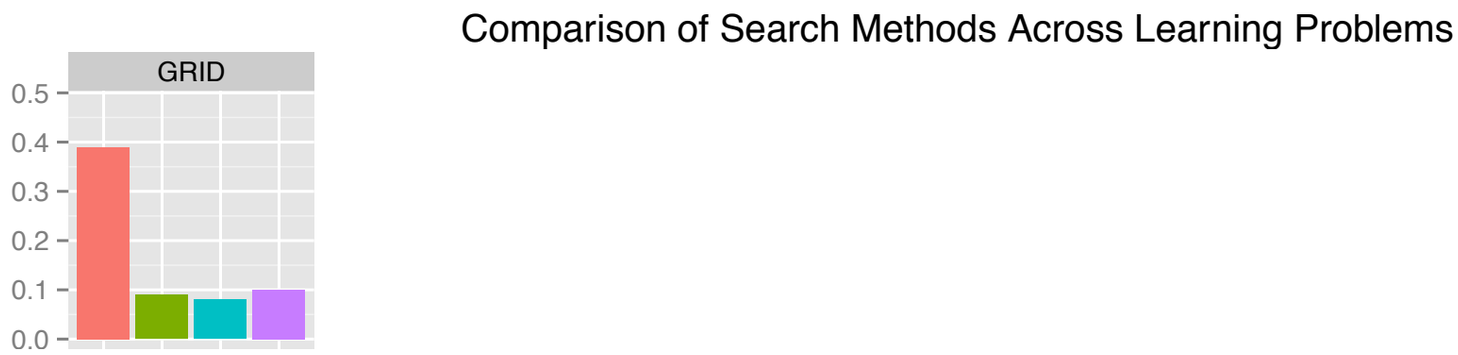

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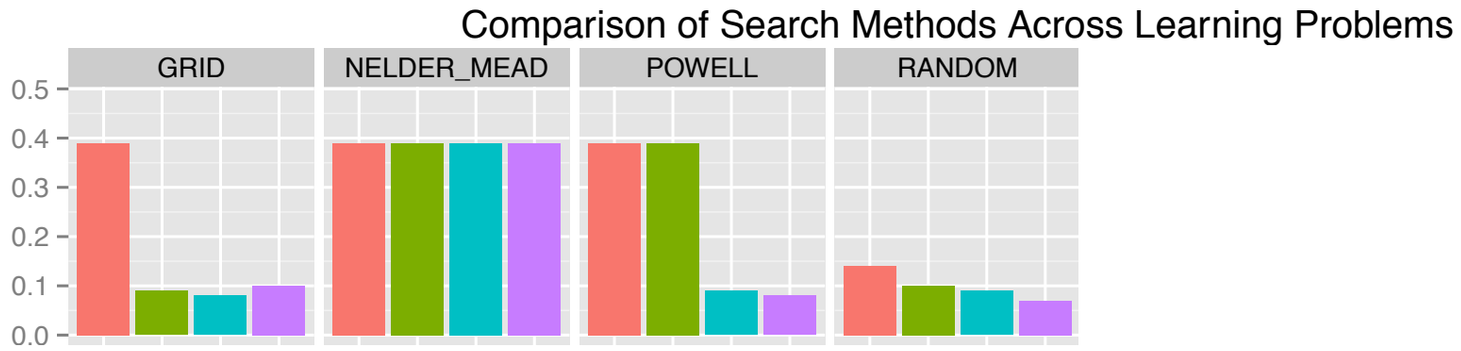

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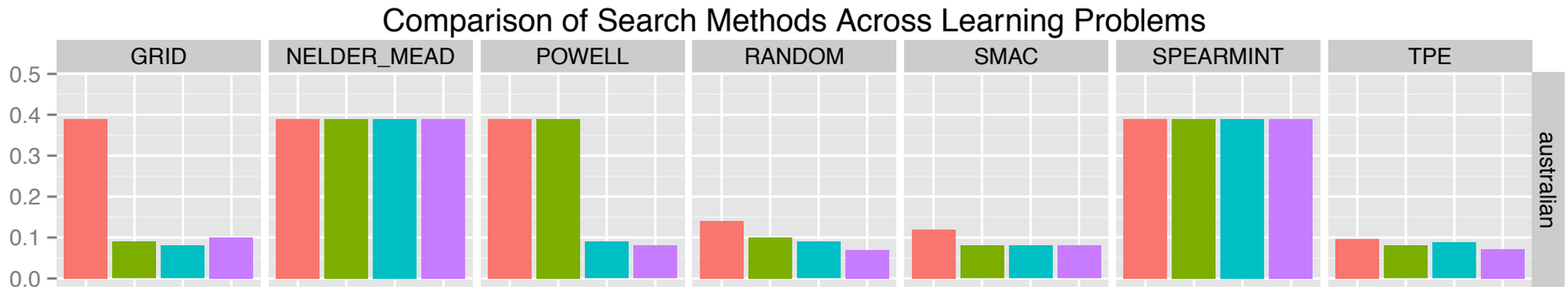

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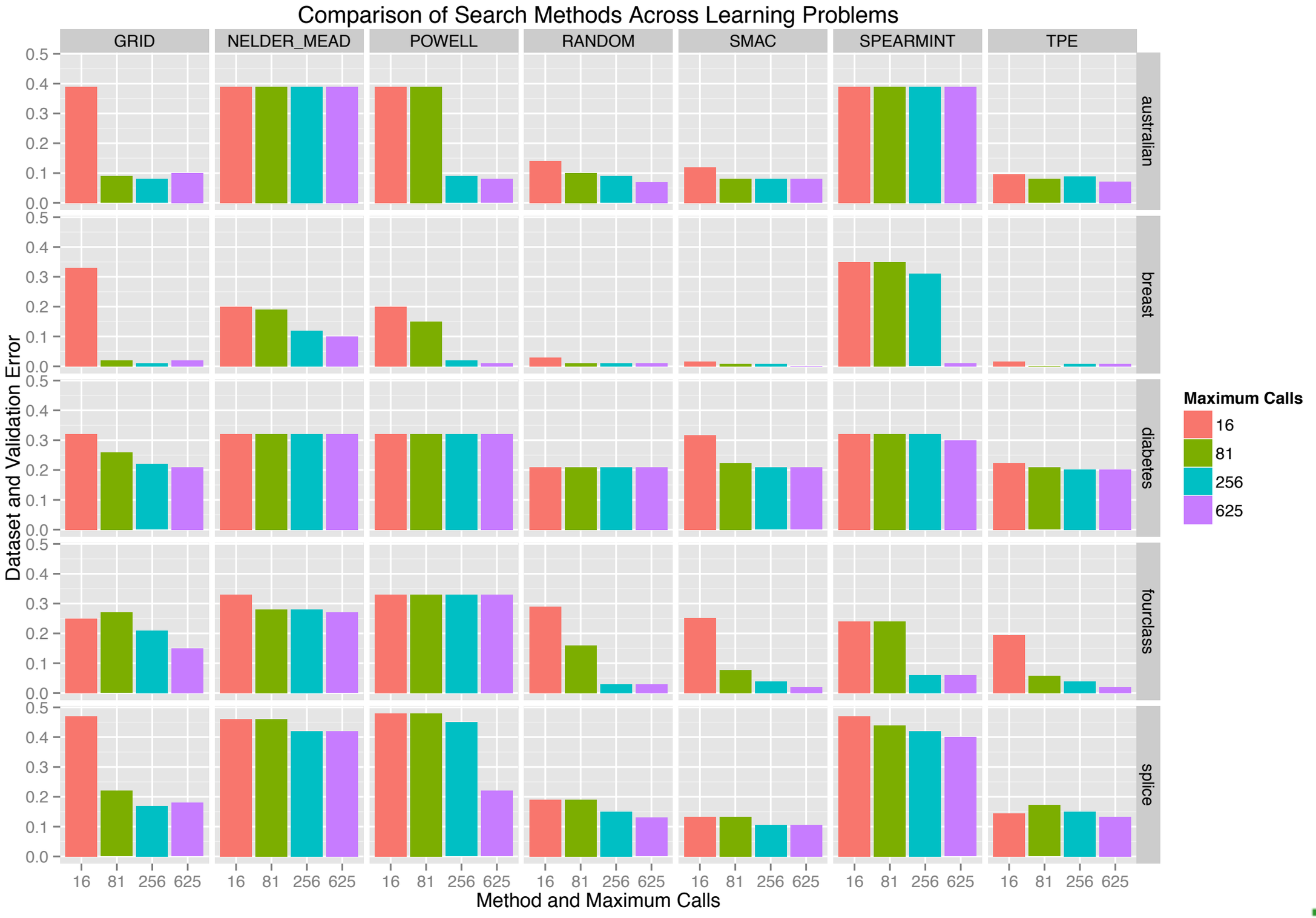

DATABRICKS

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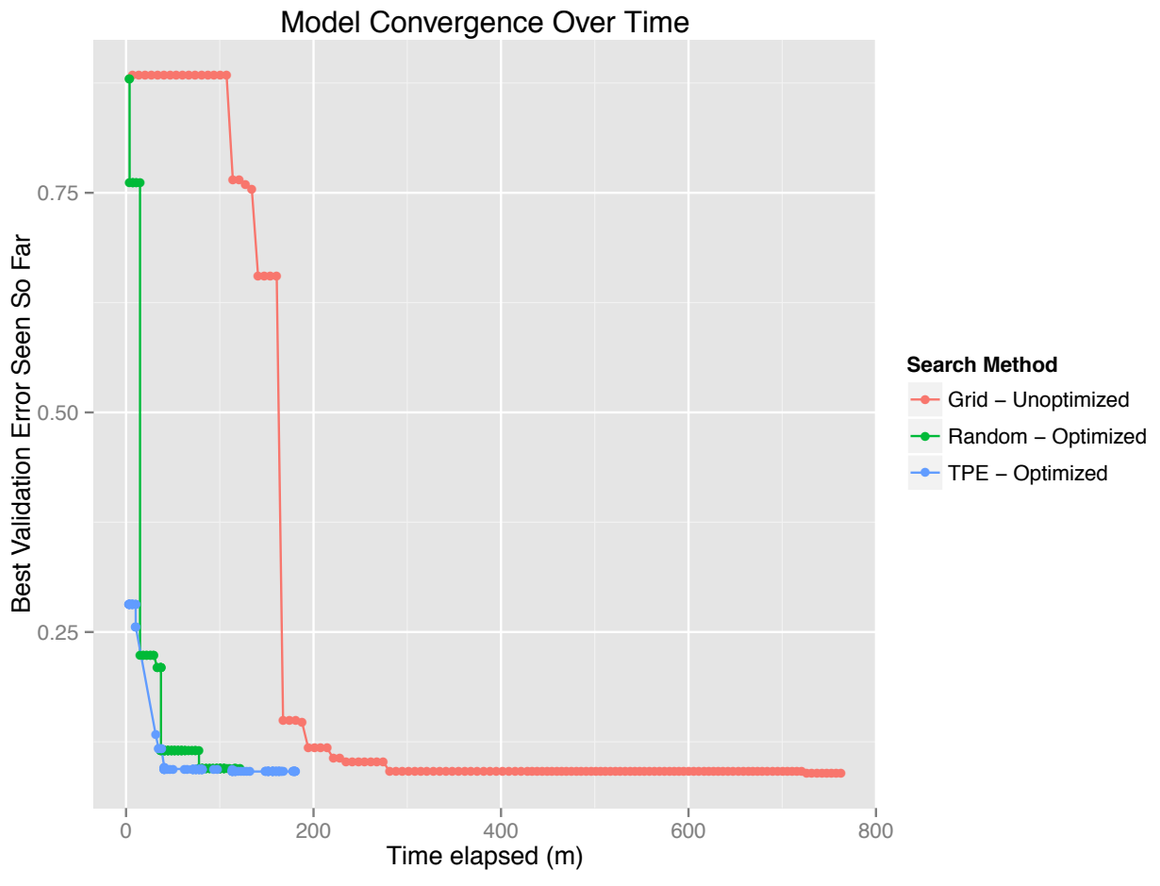

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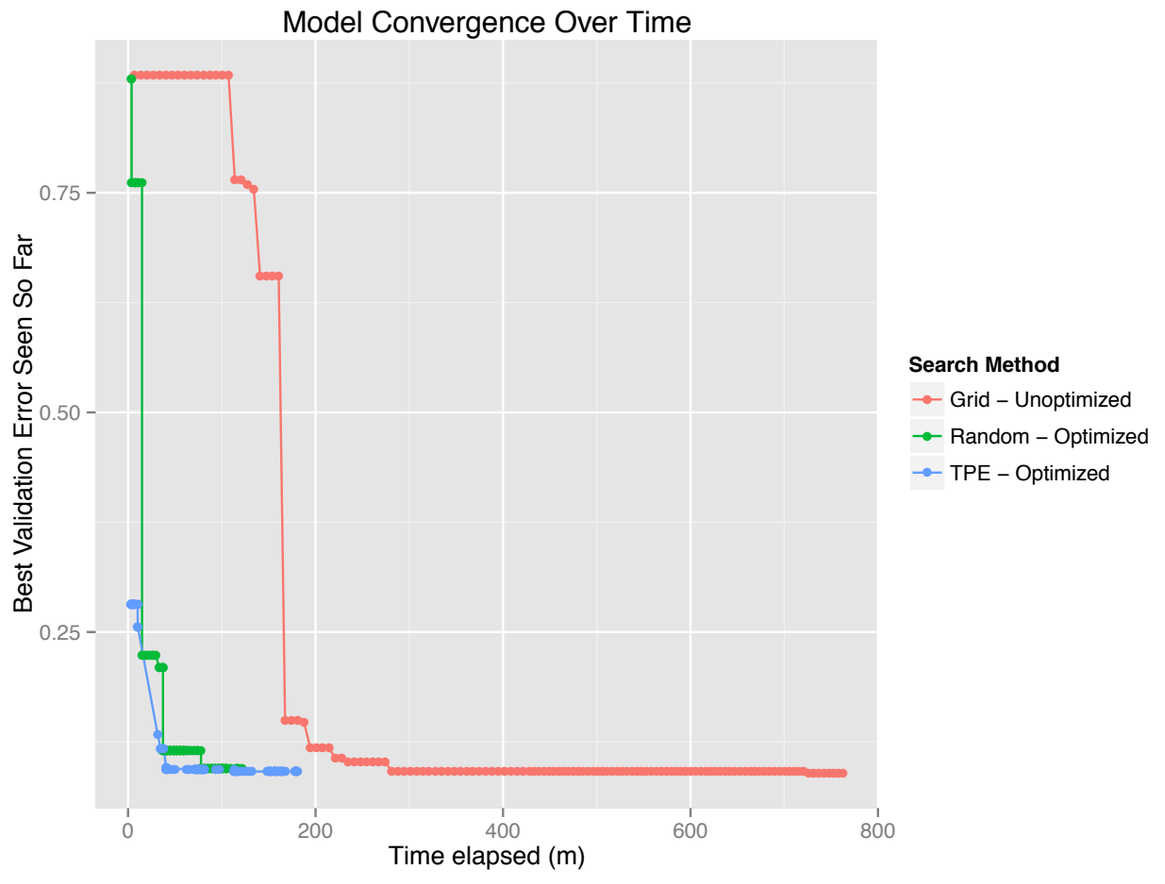
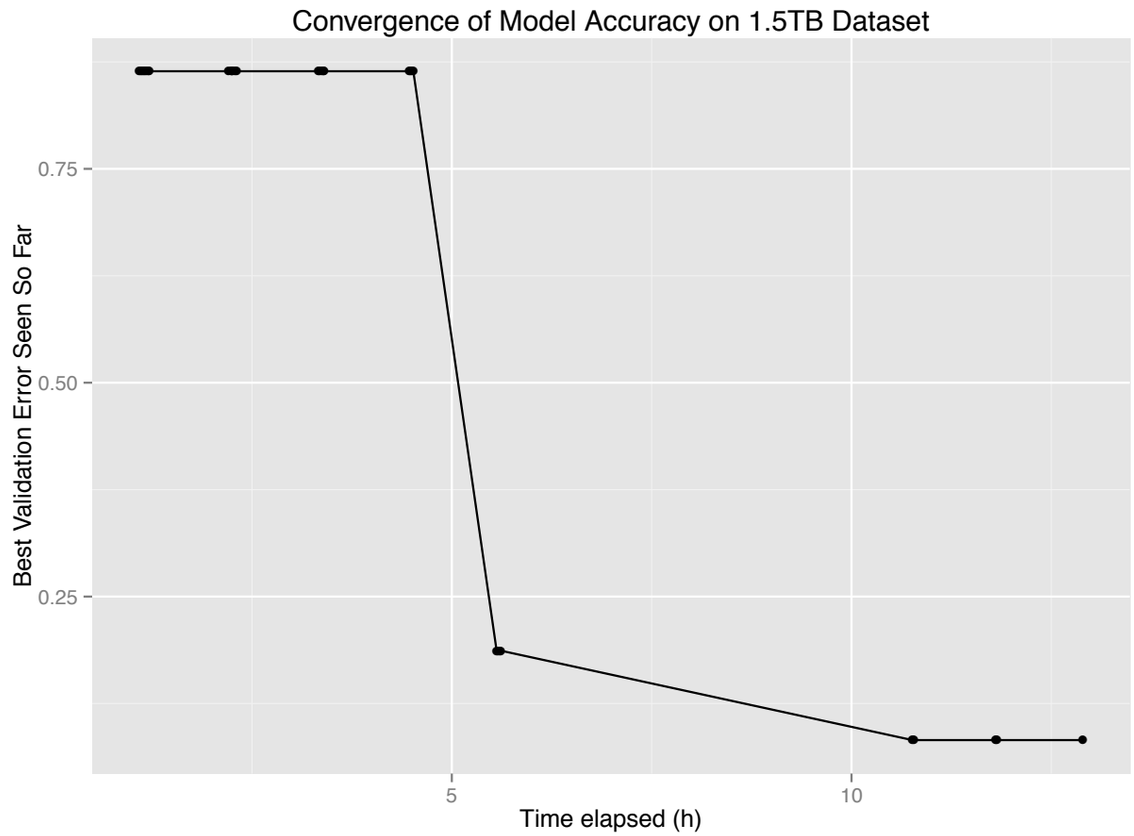


20x speedup compared to grid search

15 minutes vs 5 hours!

DATABRICKS

Does It Scale?



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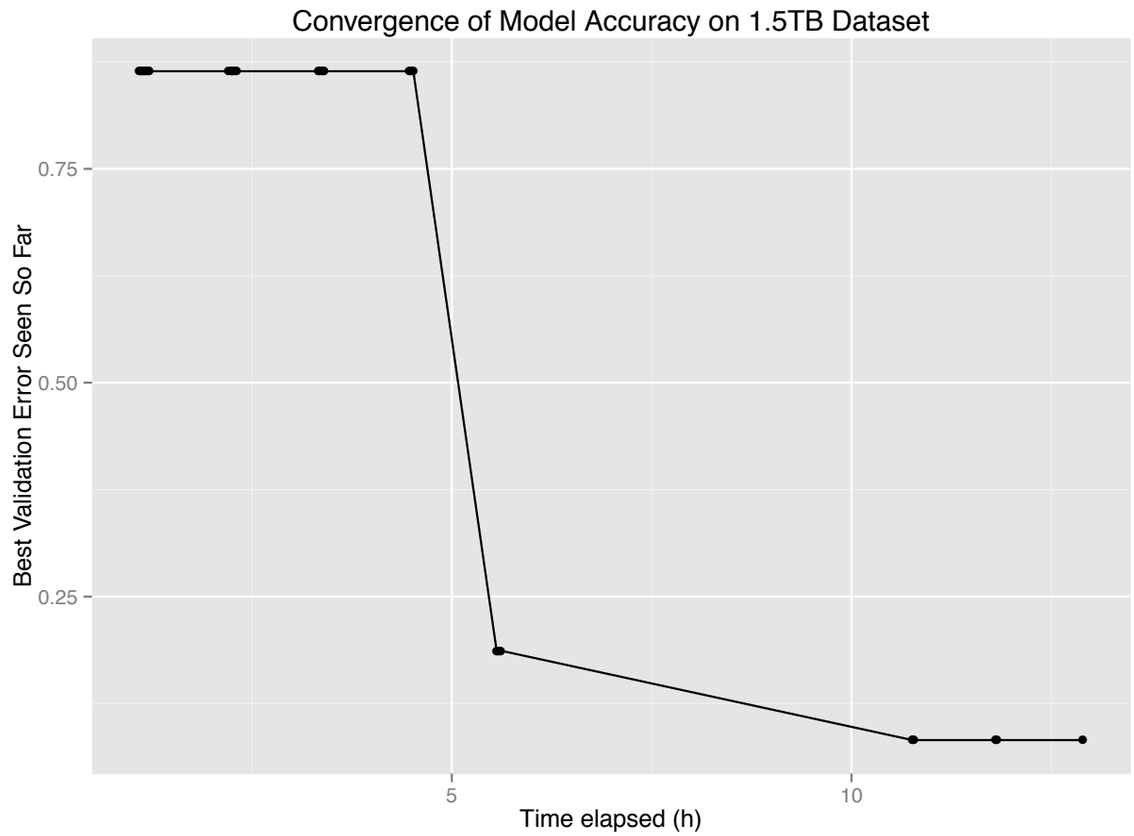
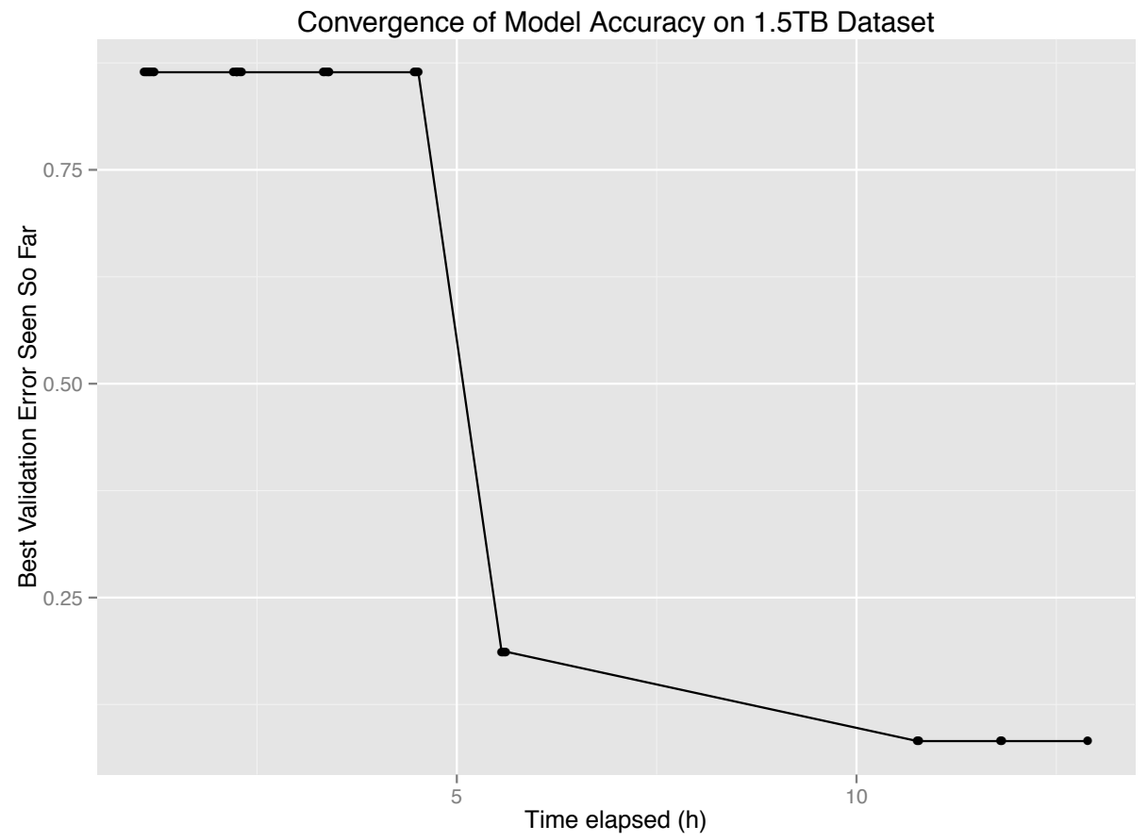


DATABRICKS

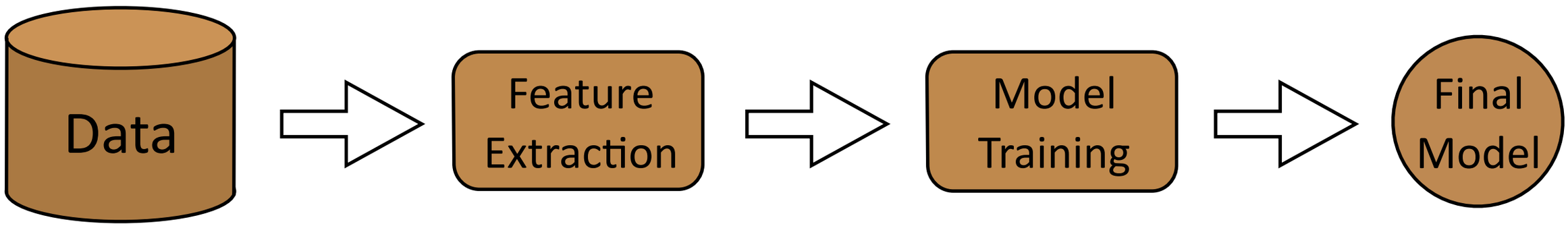
Does It Scale?

- 1.5TB dataset (1.2M x 160K)
- 128 nodes, thousands of passes over data
- Tried 32 models in 15 hours
  - Good answer after 11 hours



DATABRICKS

Future Work



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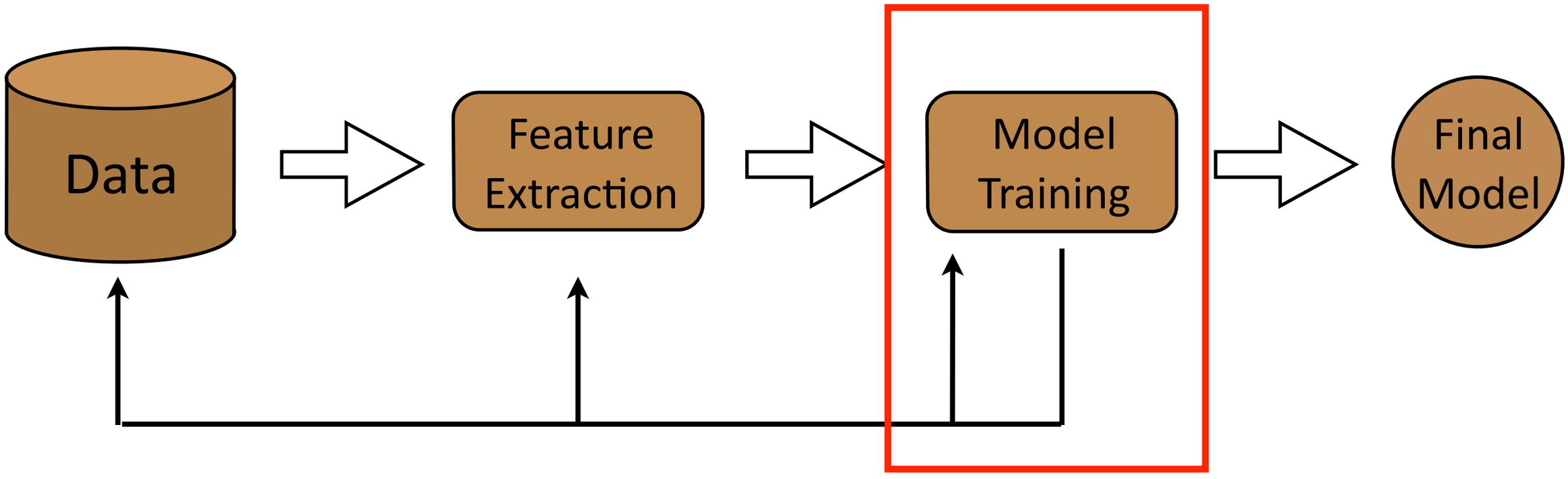

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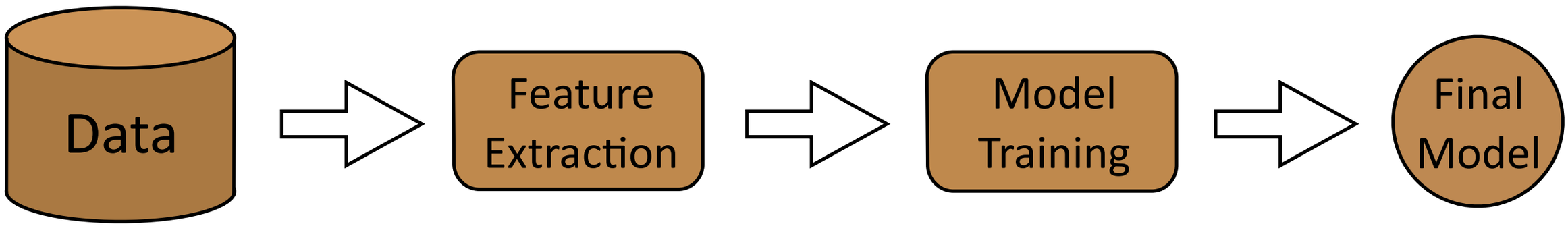

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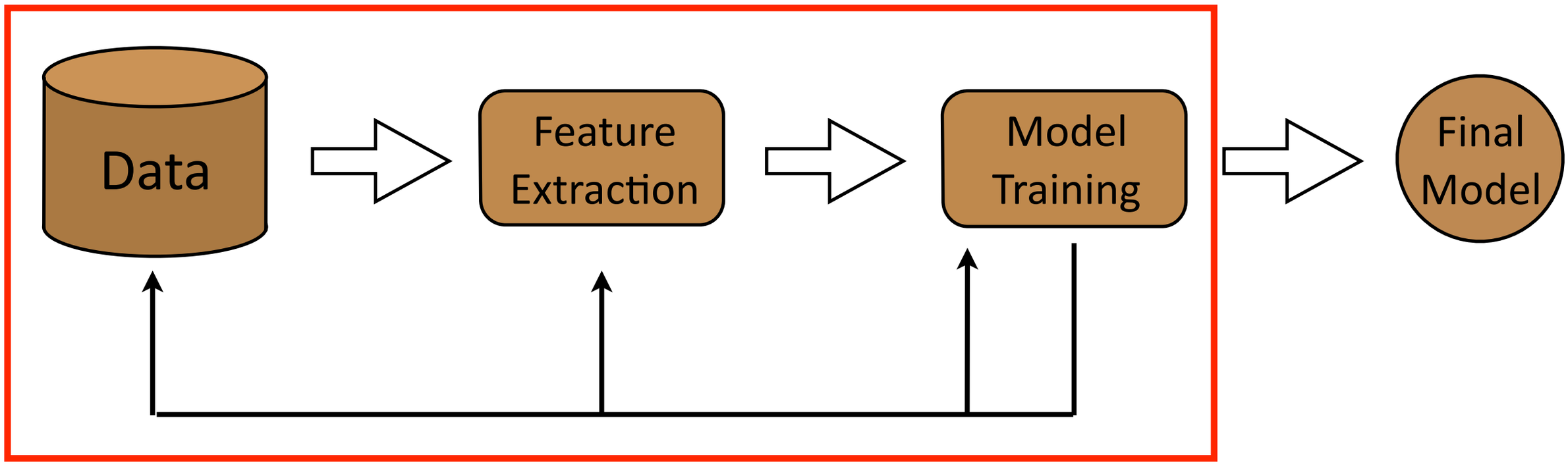
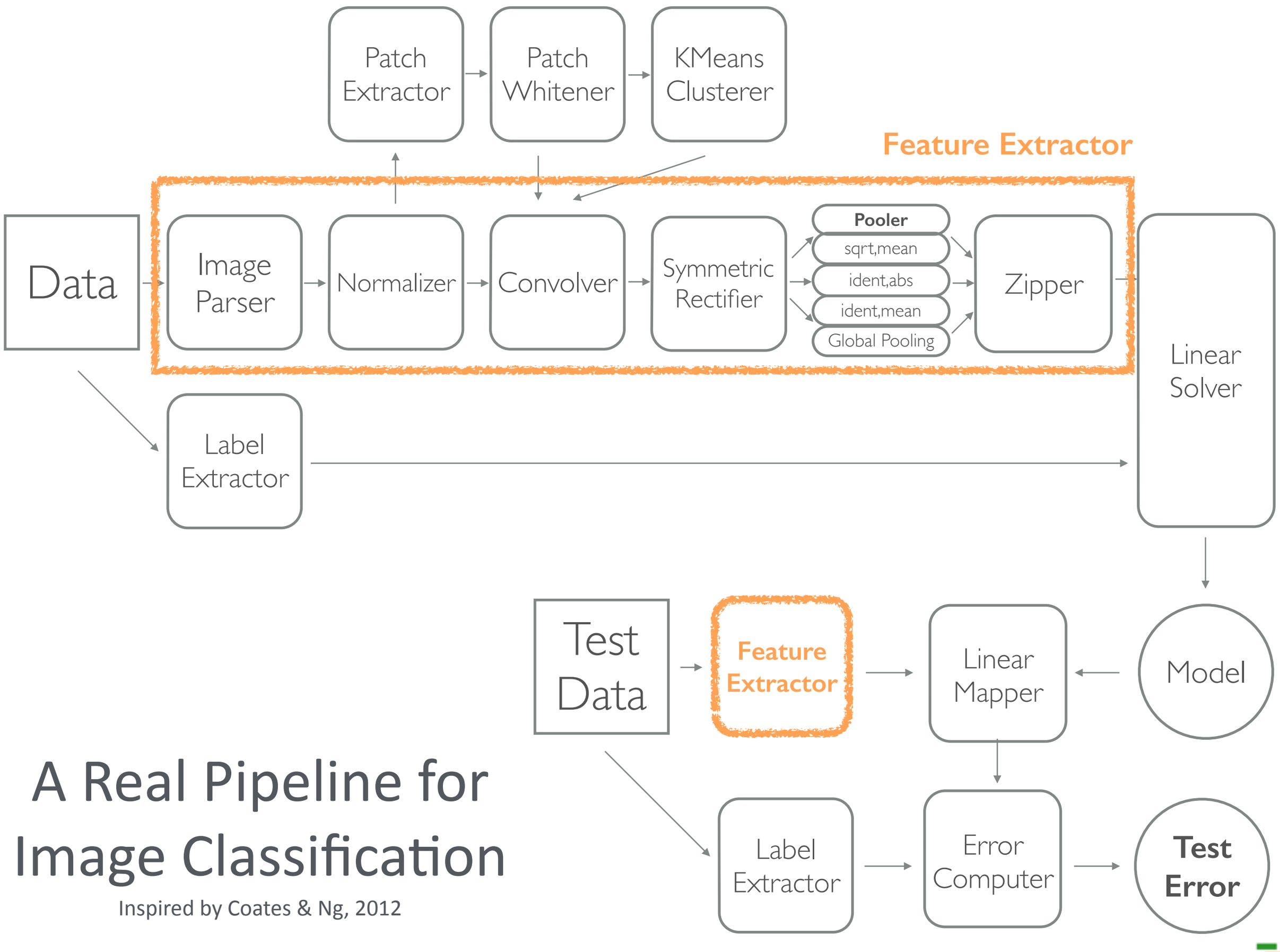


Automated ML Pipeline Construction

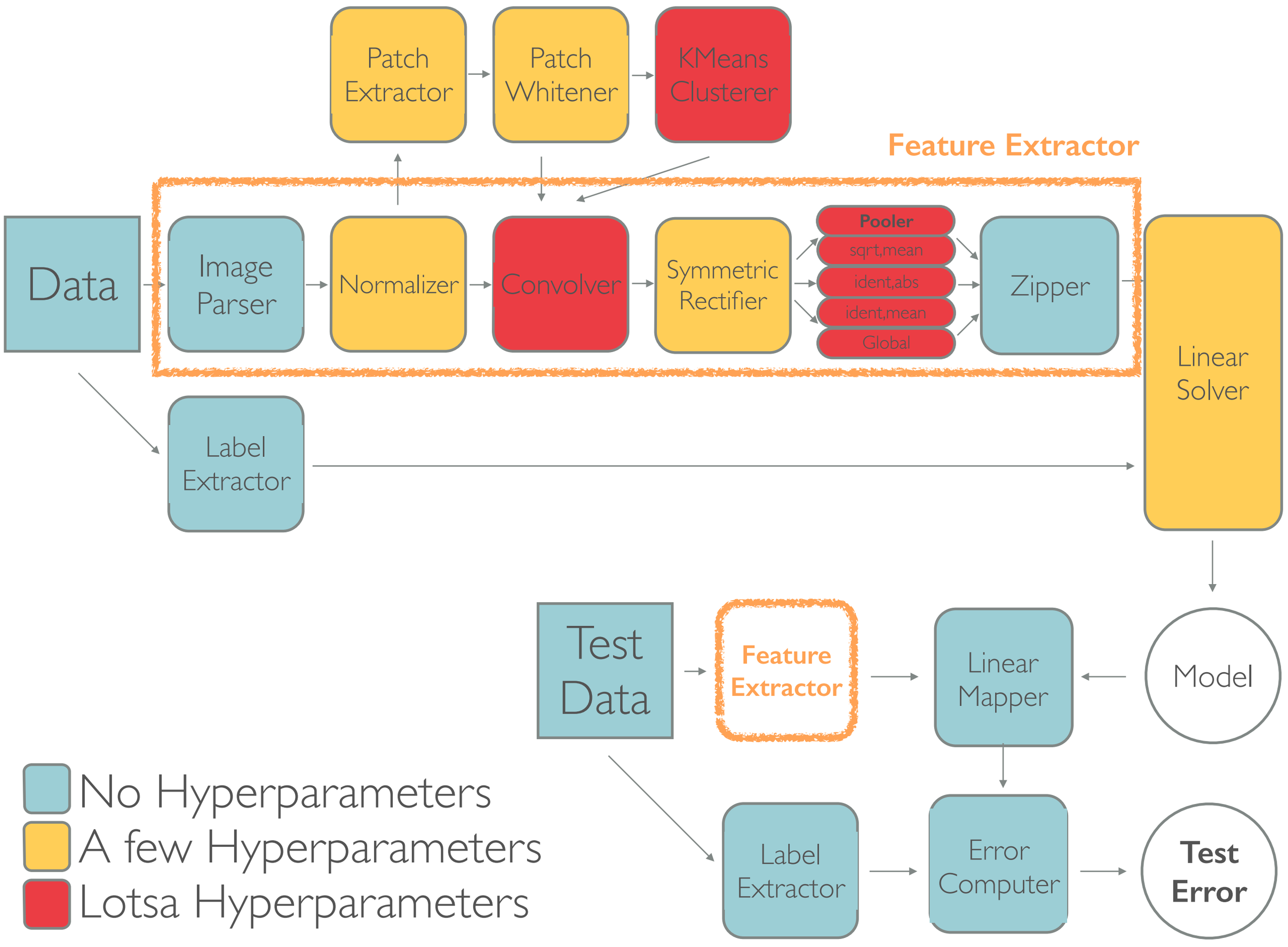
A Real Pipeline for Image Classification

Inspired by Coates & Ng, 2012



Slide courtesy of Evan Sparks

DATABRICKS



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Other Future Work

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- ✦ Ensembling

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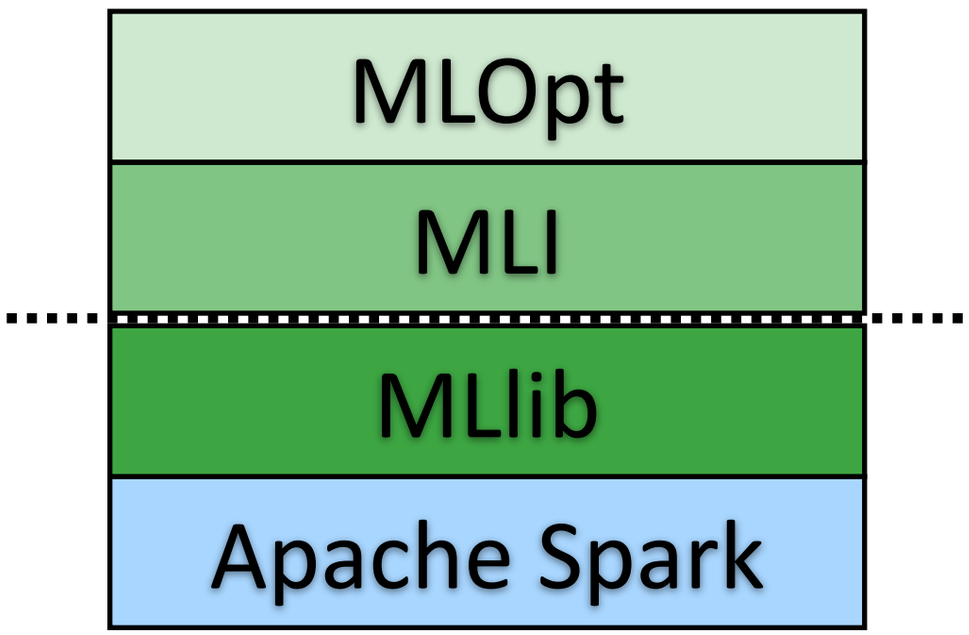

MLOpt: Declarative layer that aims to automate ML pipeline construction

MLlib: Spark's core ML library

MLI: API to simplify ML development

Spark: Cluster computing system designed for iterative computation

THANKS!
QUESTIONS?

www.mlbase.org

DATABRICKS