Factorized Machine Learning: Paths and Roadblocks

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Factorized Databases Workshop

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Golden Age of ML Analytics

Golden Age of ML Analytics

Healthcare

Insurance

Retail

Sciences

Golden Age of ML Analytics

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MAYO CLINIC
Healthcare

AMERICAN FAMILY INSURANCE
Insurance

Walmart
Retail


Sciences

$ 38 billion
in 2019*

$ 500 billion
by 2025*

*International Data Corporation

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Still, fundamental **efficiency and usability bottlenecks** in the **end-to-end process** of building and deploying ML applications

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My Research

New abstractions, algorithms, and software systems
to "***democratize***" ML-based data analytics from
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Democratization = System Efficiency (Reduce costs) + Human Efficiency (Improve productivity)

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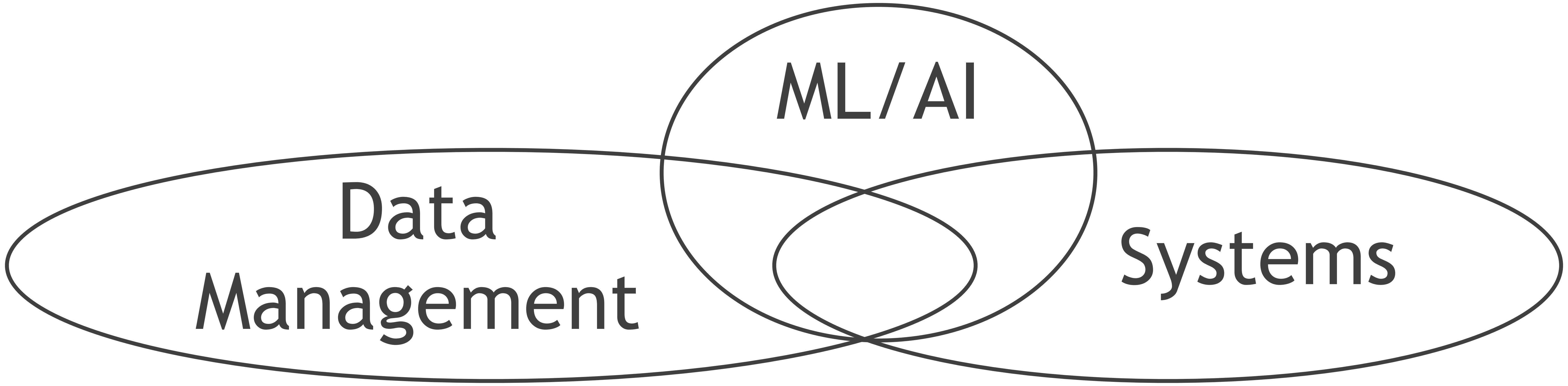


My Research

New abstractions, algorithms, and software systems to "*democratize*" ML-based data analytics from a data management/systems standpoint

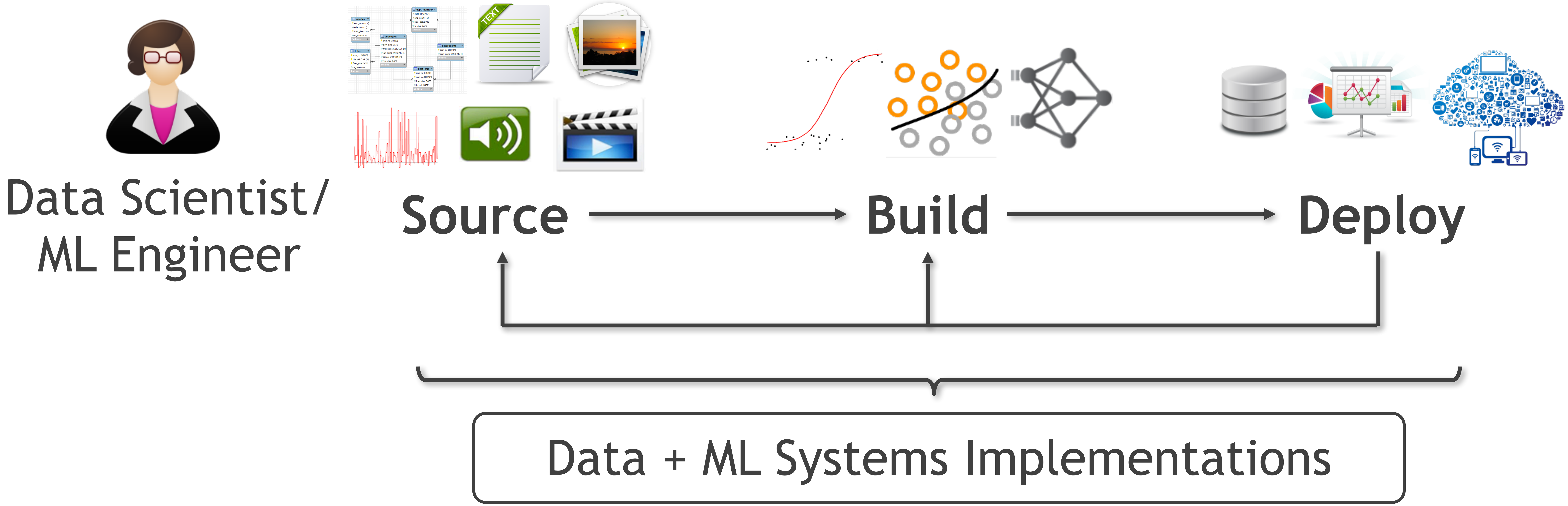
Democratization = System Efficiency (Reduce costs) + Human Efficiency (Improve productivity)

Practical and scalable data systems for ML analytics

Inspired by *relational database systems* principles

Exploit insights from *learning theory* and *optimization theory*

End-to-End ML Application Lifecycle



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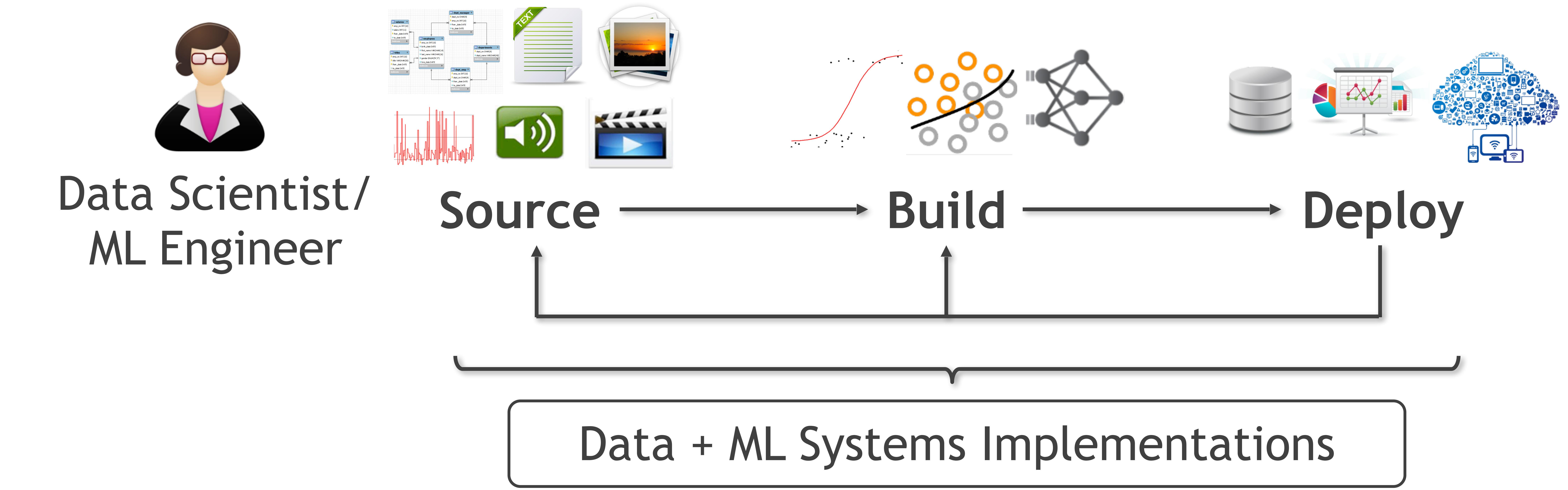

Research Approach : ***Abstract*** key steps + ***Formalize*** computation + ***Automate*** grunt work + ***Optimize*** execution

https://ADALabUCSD.github.io

Outline

- Introducing ML over Joins
  - Orion: Factorized ML
  - Morpheus and Extensions
- Roadblocks and Musings

Outline

4m Introducing ML over Joins

4m Orion: Factorized ML

10m Morpheus and Extensions

4m Roadblocks and Musings

ML after Joins: The Problem

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A fundamental bottleneck in feature engineering on structured data:

Many datasets are multi-table ⟷ ML toolkits assume single-table inputs

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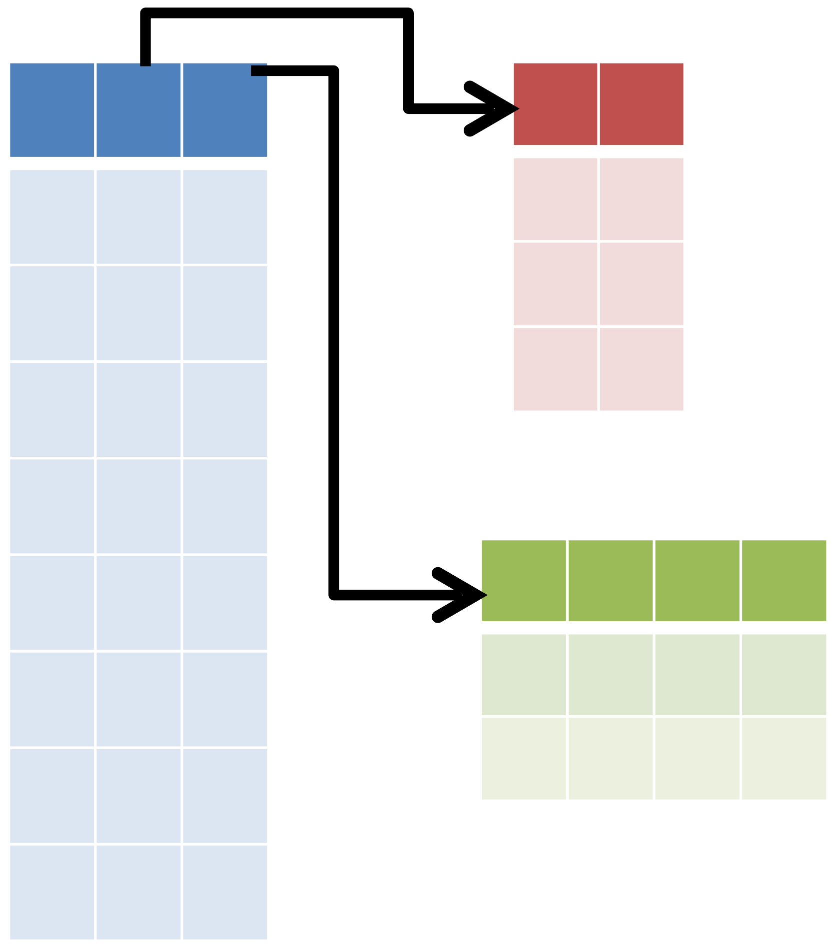

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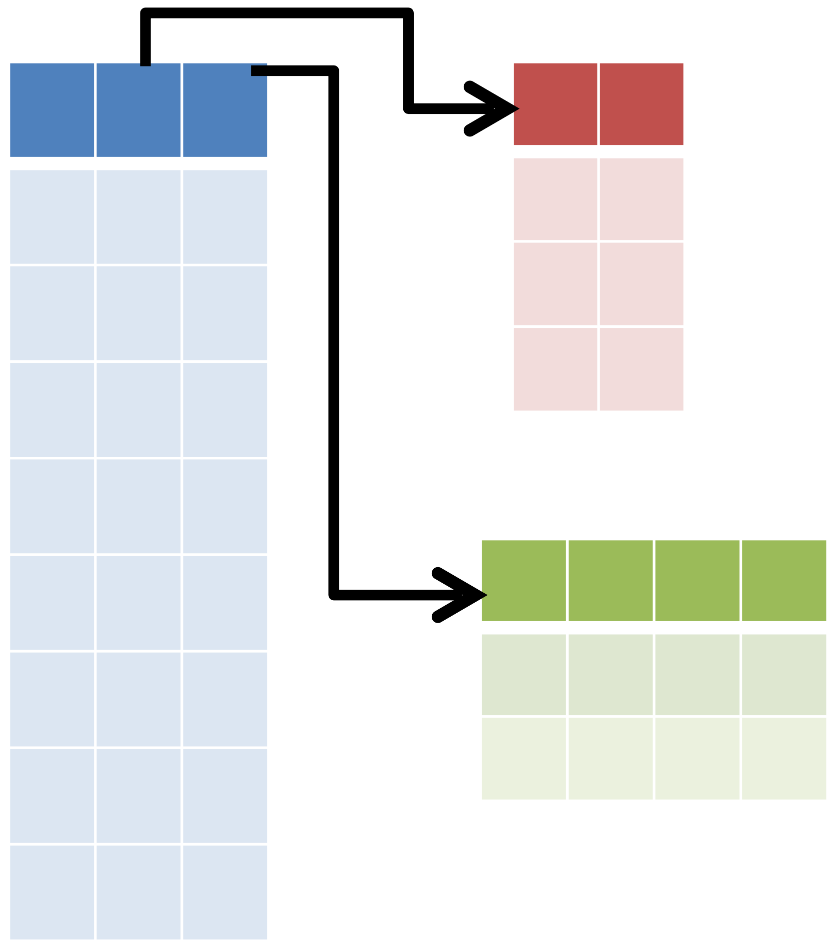
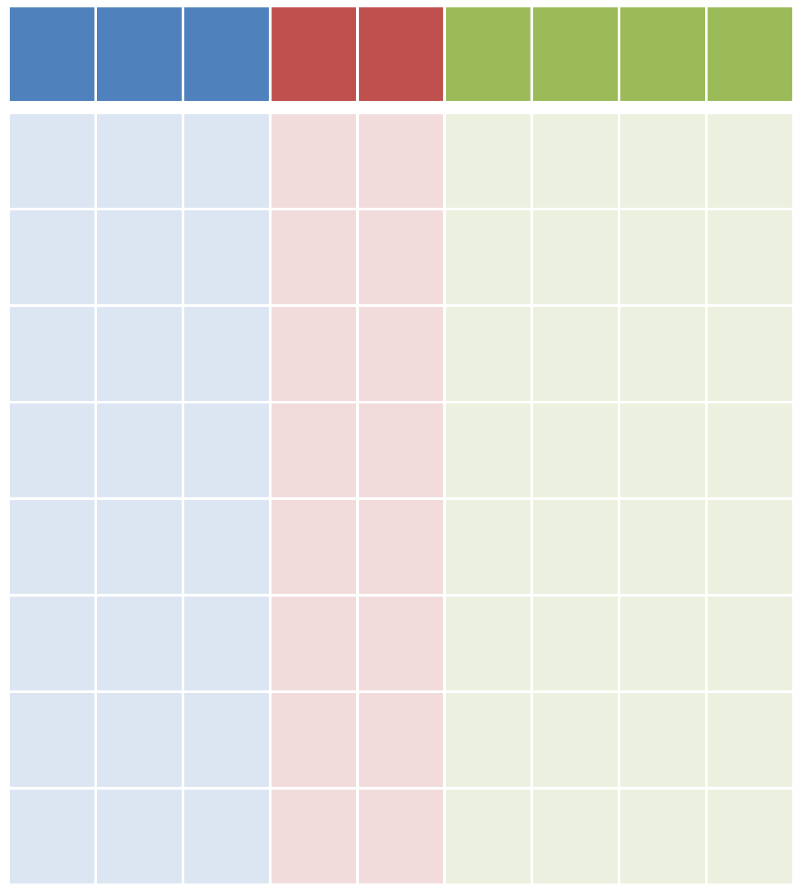


Key-Foreign Key (KFK) Joins



✖ System efficiency

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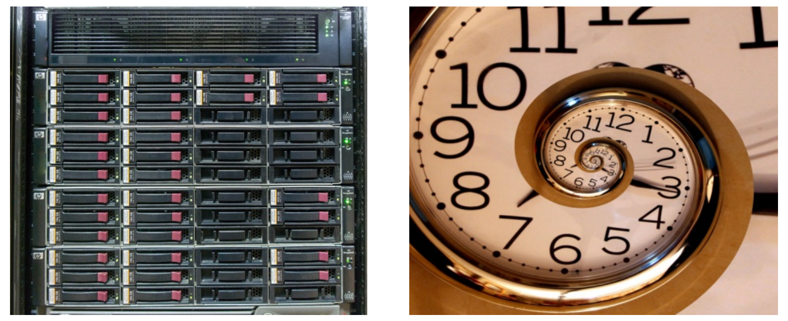

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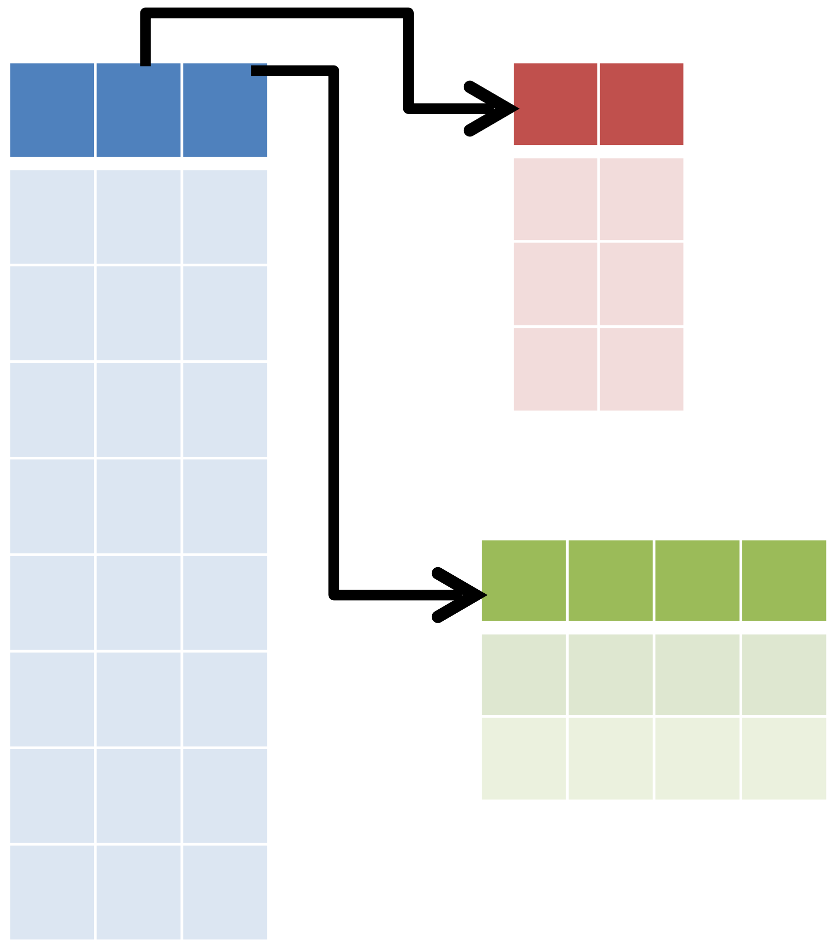

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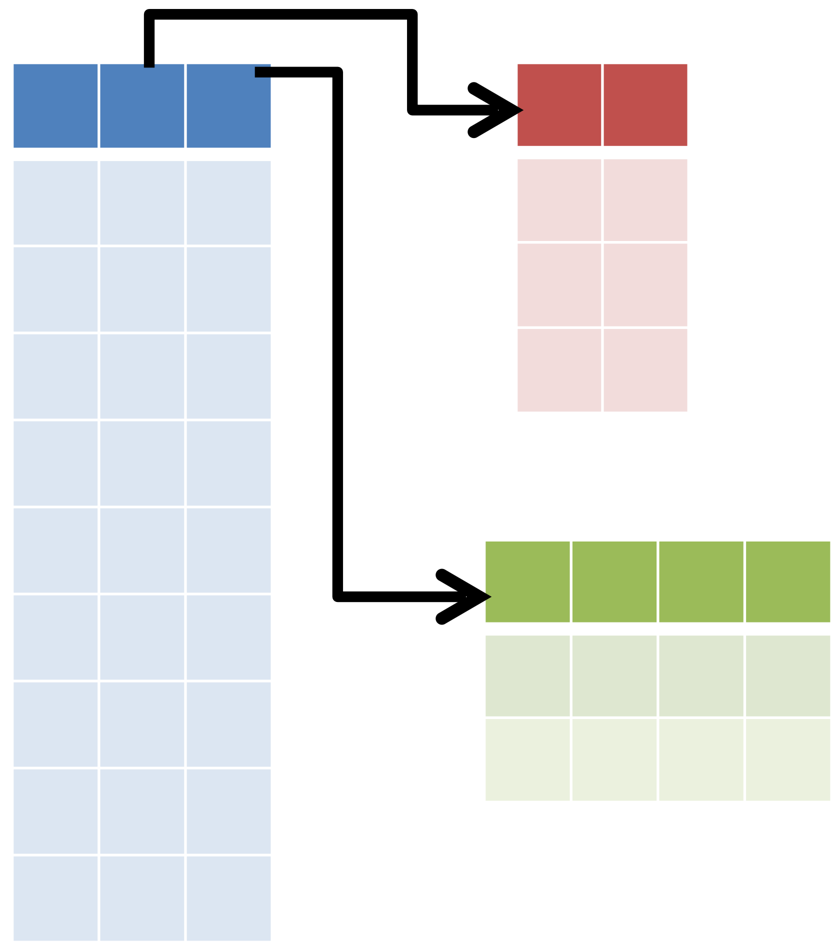

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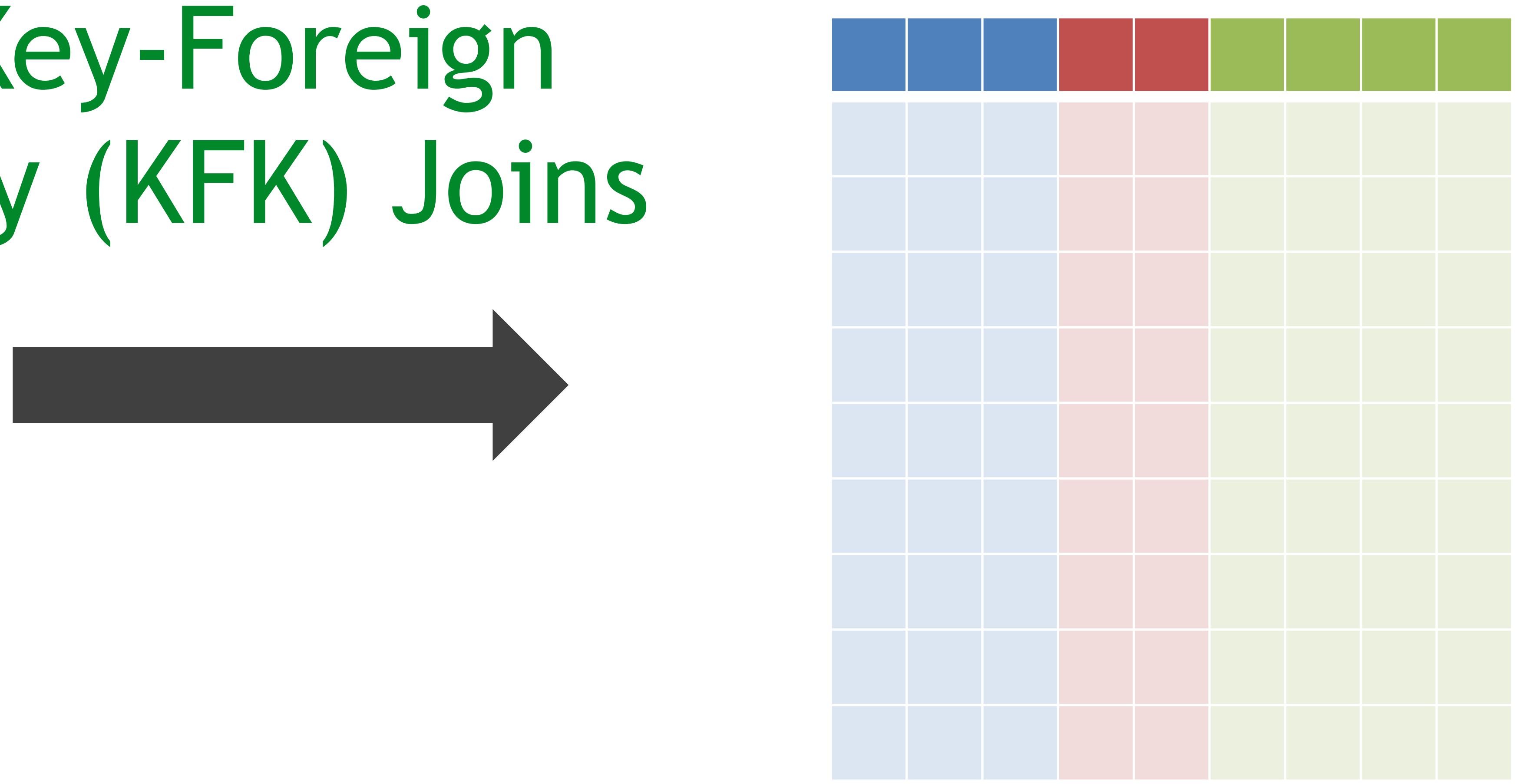

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Avoid Joins **Physically**

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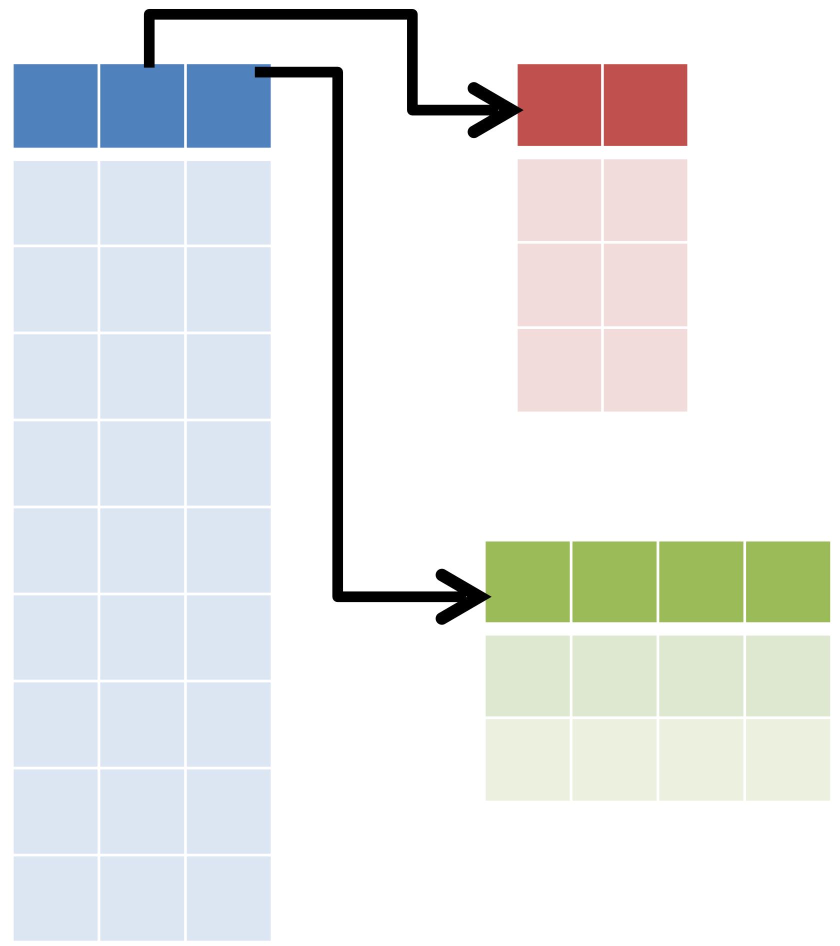

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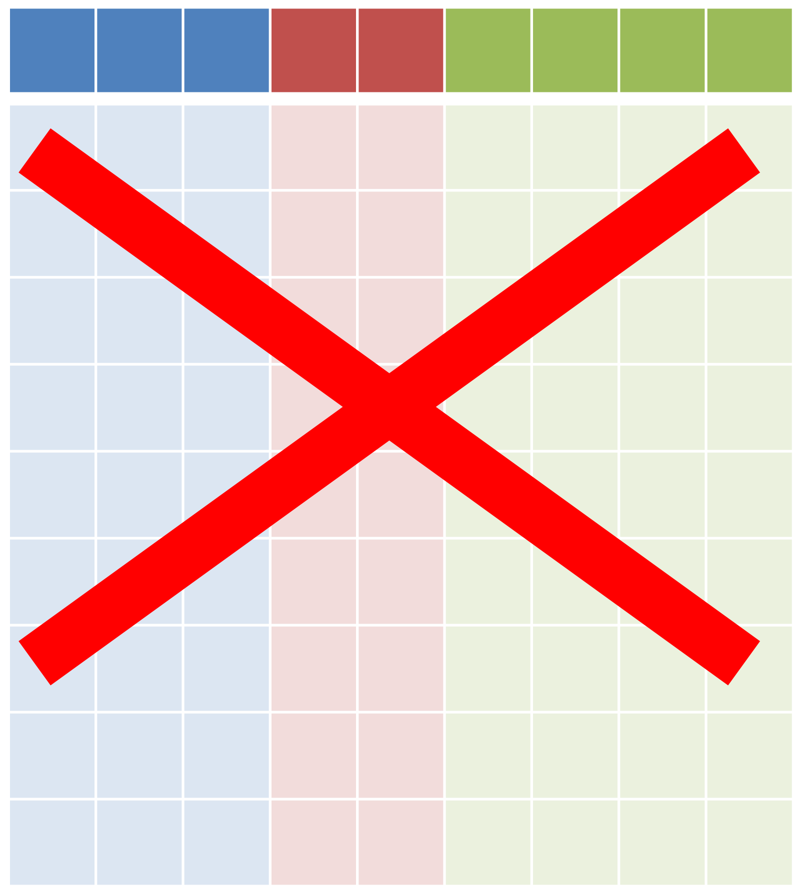

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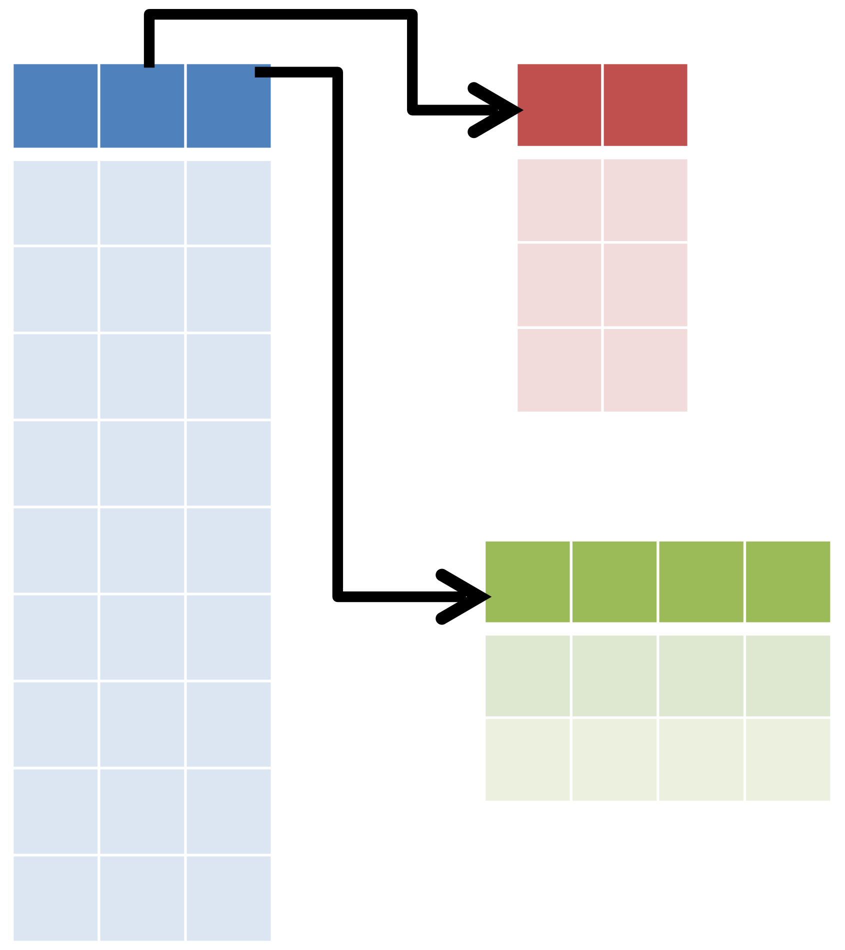

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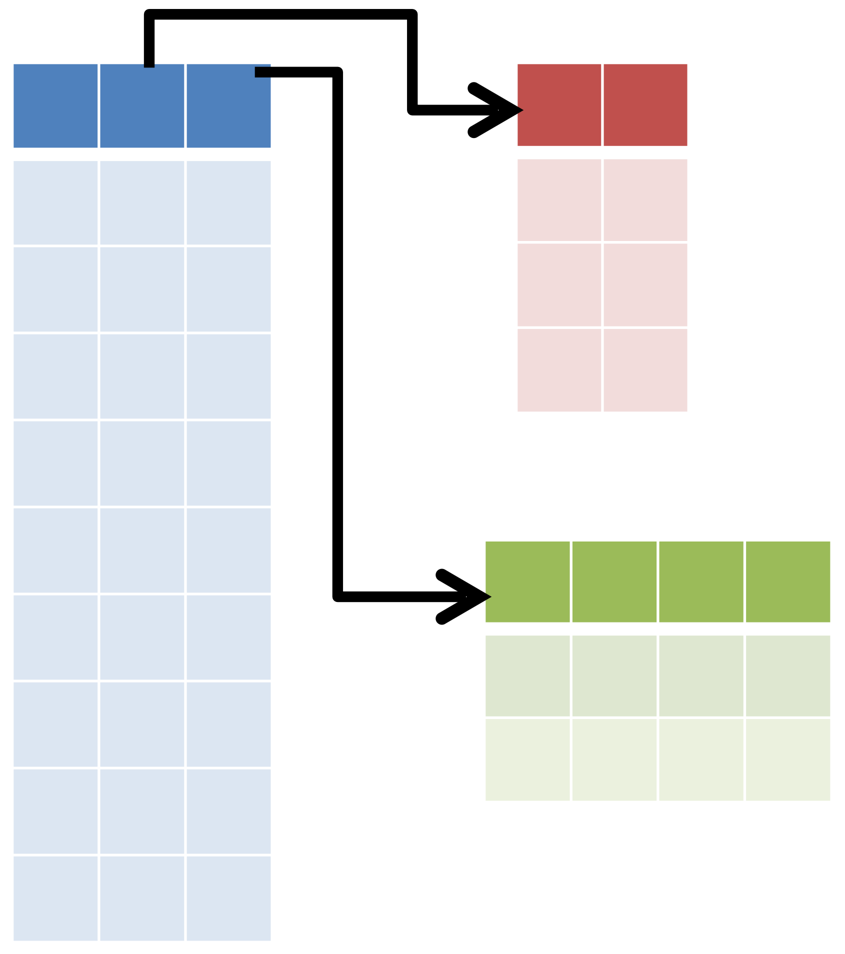

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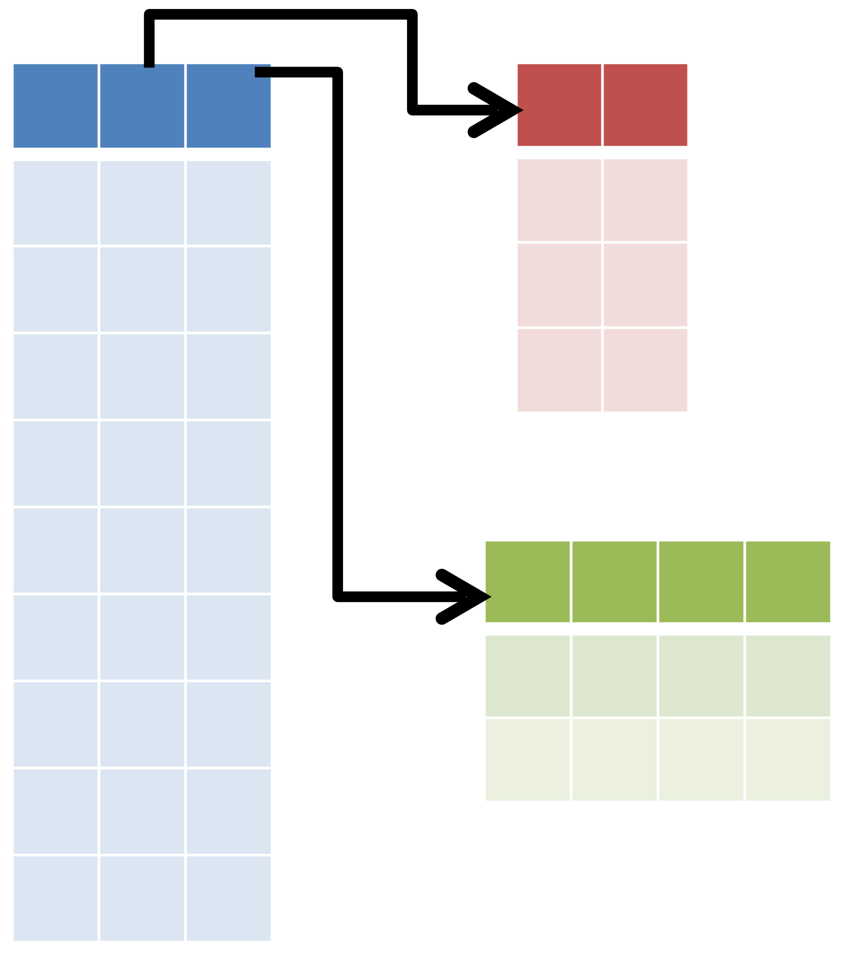

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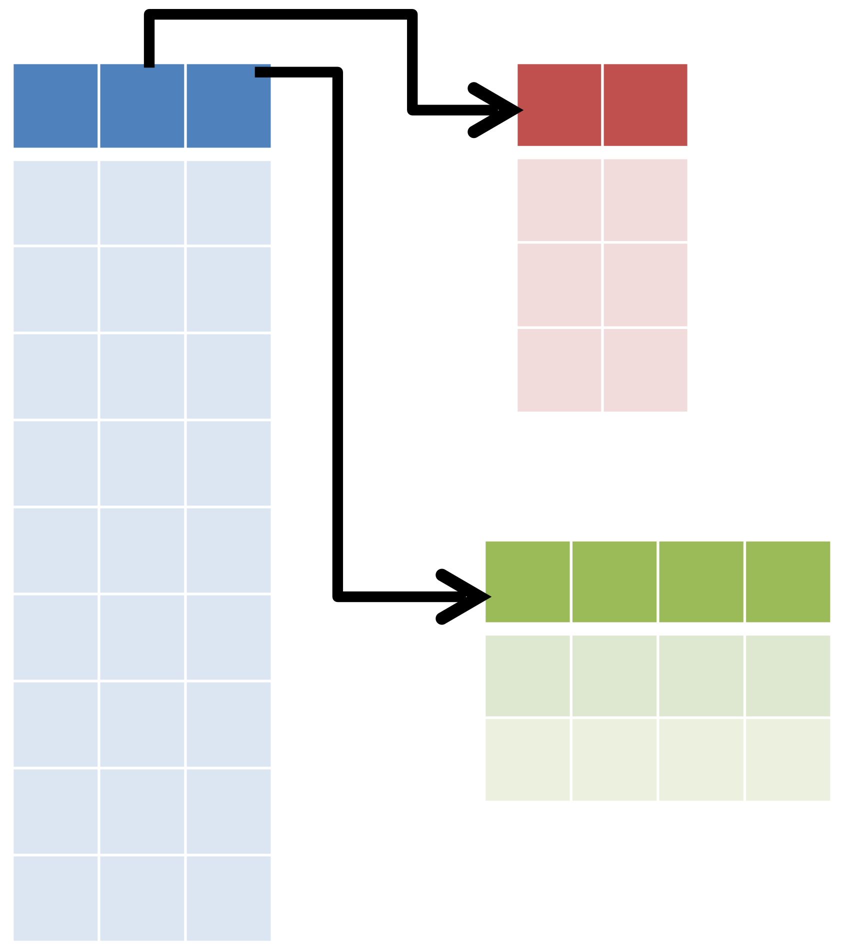

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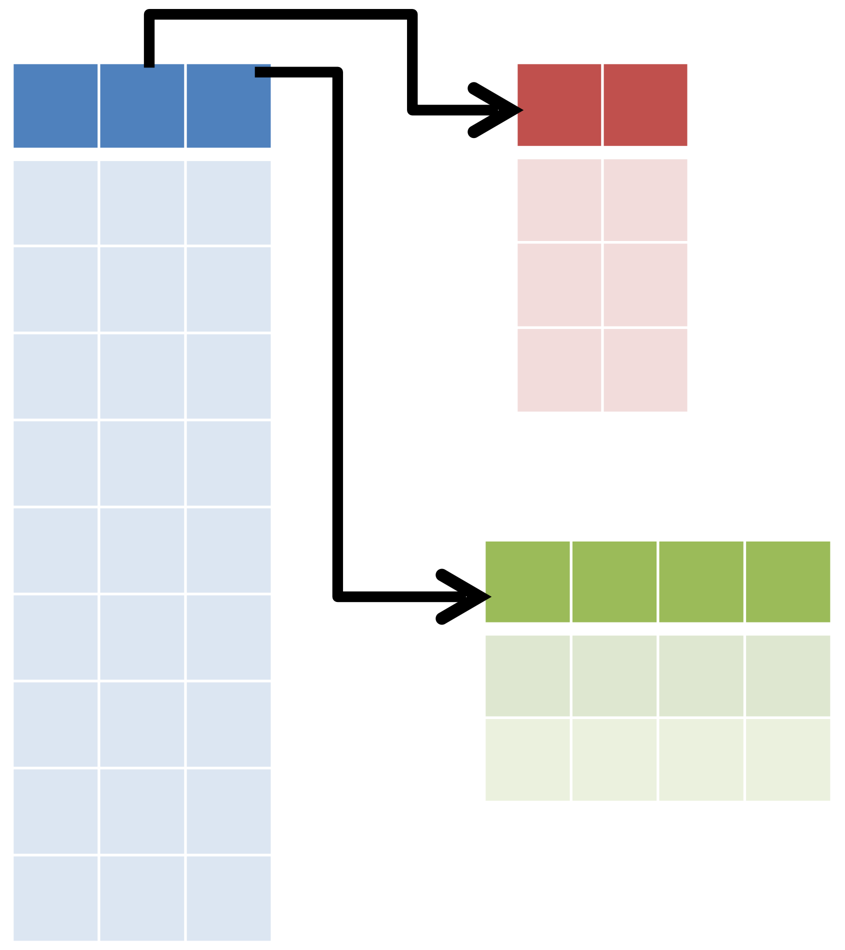

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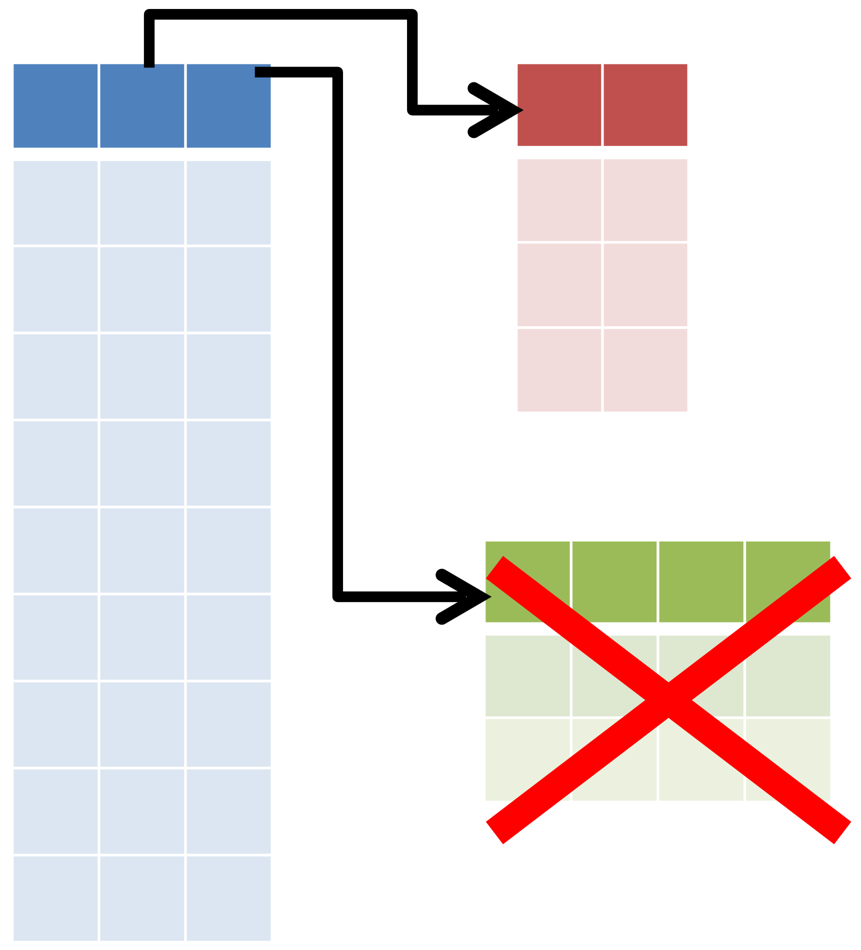

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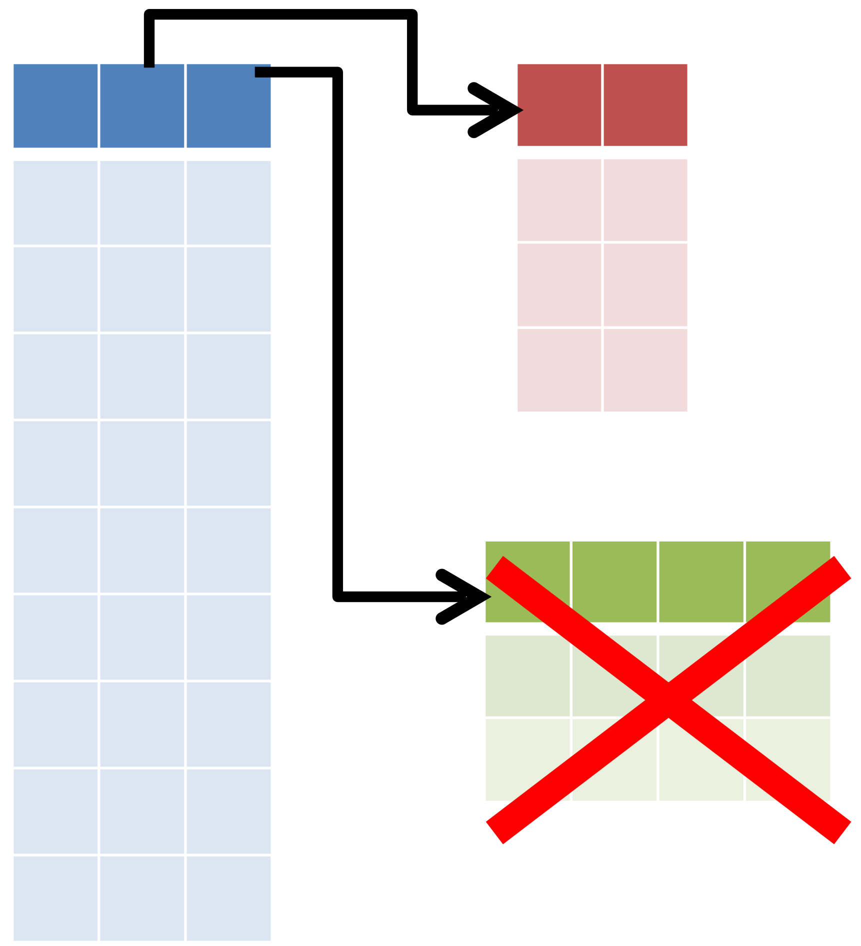

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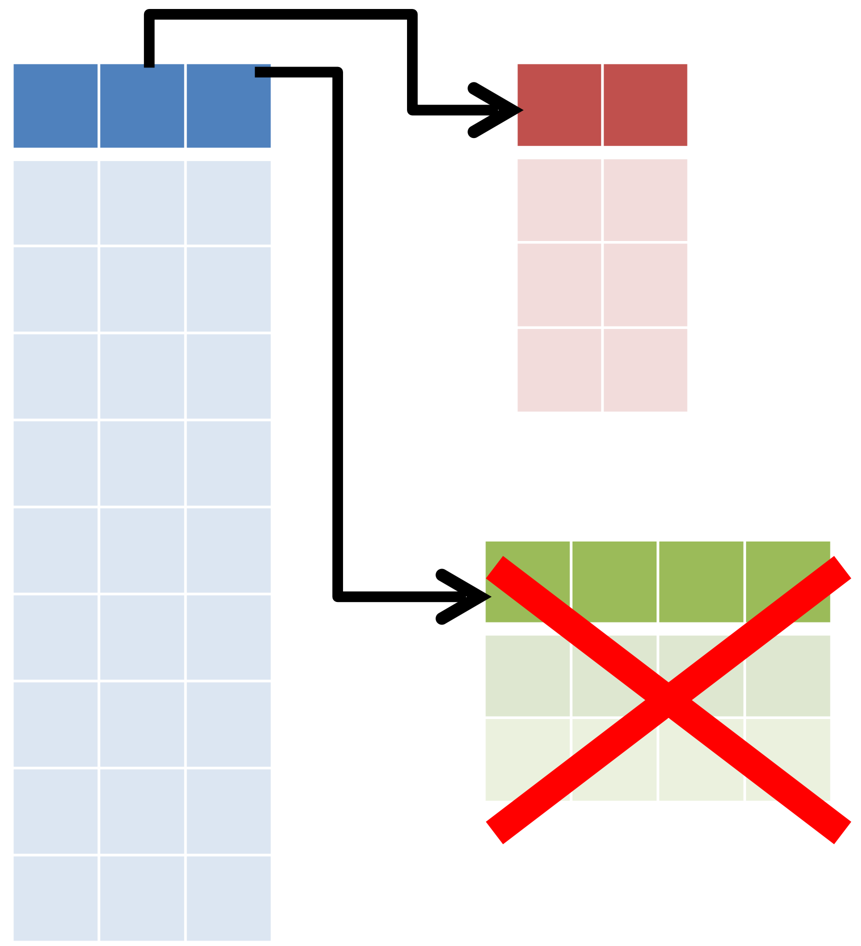

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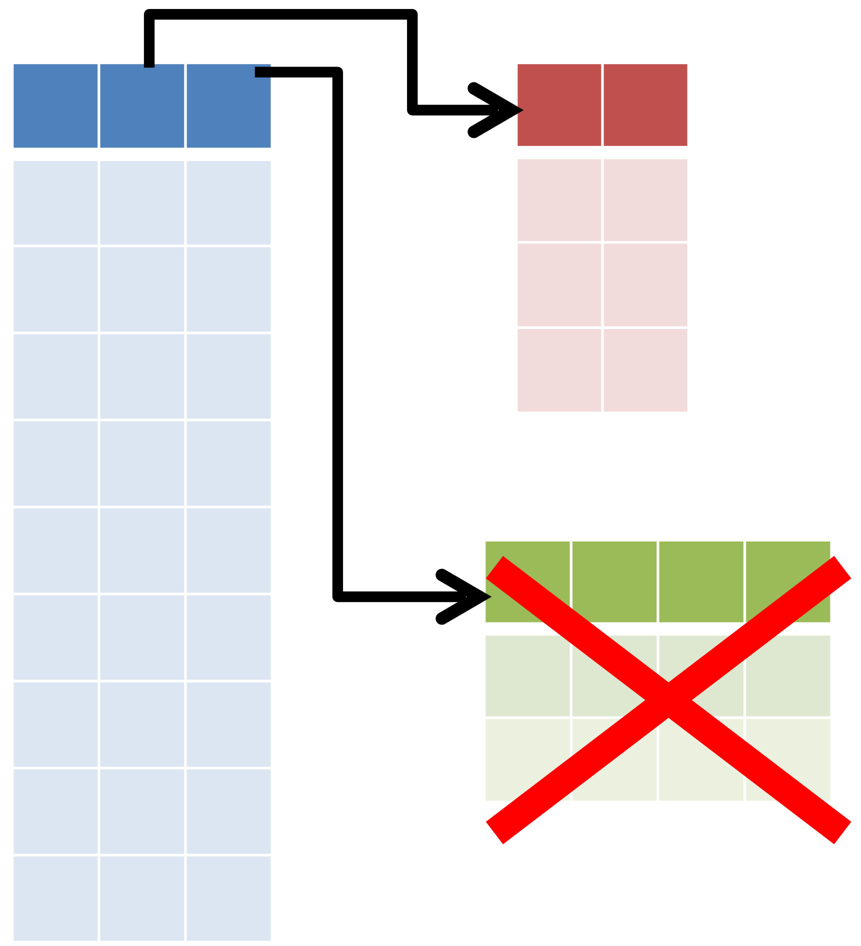

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Running Example for ML over Joins

ML Task: Classify if a customer will *churn* or not

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Customers — Foreign Key → Employers

CID	Churn?	Gender	Age	EmpID
1	Yes	Female	33	AMZN
2	No	Male	51	GOOG
3	Yes	Other	46	GOOG
4	No	Female	27	MSFT
…	…	…	…	…

EmpID	State	Revenue
AMZN	WA	136b
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More features!

More joins possible, e.g., with neighborhood data, weather data, etc.

*Materializing such joins can blow up the data, **even by over 10x**!*

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4m Introducing ML over Joins

4m Orion: Factorized ML

10m Morpheus and Extensions

4m Roadblocks and Musings

ORION: Factorized ML

Learning Generalized Linear Models over Normalized Data. **SIGMOD 2015**

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Insight: Decompose ML computations and push them down through joins

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$$\boldsymbol{w}^T \mathbf{x} = [\boldsymbol{w}_C^T\ \boldsymbol{w}_E^T]\begin{bmatrix}\mathbf{x_C}\\ \mathbf{x_E}\end{bmatrix} = \boldsymbol{w}_C^T \mathbf{x_C} + \boldsymbol{w}_E^T \mathbf{x_E}$$

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1 full iteration requires 2 scans of Employers, 1 scan of Customers

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Challenges Tackled: Scalability; developability

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Demonstration of Santoku: Optimizing Machine Learning over Normalized Data. **VLDB 2015**

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Prototyped on PostgreSQL with UDAFs (MADlib style)

Distributed prototype with MapReduce on Hive & Spark (MLlib style)

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Explored for production use cases:

Microsoft (Web security)

LogicBlox (Retail)

Google (Ads)

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Q: *Can we avoid manual rewriting of each ML algorithm and "automate" factorized ML on top of ML tools?*

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MORPHEUS: Generalizing ORION

Towards Linear Algebra over Normalized Data. **VLDB 2017**

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Goal: *Automate* factorized ML to many ML algorithms in a unified way

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Create a framework for rewrite rules for LA ops

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Factorized ML: Prior Work

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Factorized ML: Prior Work

Orion
(GLMs)
↓
Stack 1

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ORION (GLMs)	FDB-F (OLS)
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Spark

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The Morpheus Approach

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GLMs OLS K-Means NMF …

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ORION (GLMs) → Stack 1

FDB-F (OLS) → Stack 2

Other ML models → …

Spark

The MORPHEUS Approach

GLMs, OLS, K-Means, NMF, … → MORPHEUS: Factorized LA

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Other ML models → ...

Spark

The MORPHEUS Approach

GLMs, OLS, K-Means, NMF, ... → MORPHEUS: Factorized LA

R, NumPy, Oracle R Enterprise, TensorFlow, Apache SystemML, ...

Towards Linear Algebra over Normalized Data. **VLDB 2017**

Bulk LA-based ML Algorithms

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Ordinary Least Squares linear regression with normal equations

Input: Regular matrix T, Y, w
$w = ginv(\text{crossprod}(T))(T^{\intercal}Y)$

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Ordinary Least Squares linear regression with normal equations

Input: Regular matrix T, Y, w
$w = ginv(\text{crossprod}(T))(T^{\intercal}Y)$

Logistic regression with BGD; works for L-BFGS and Conjugate Gradient too

Input: Regular matrix T, Y, w, α
for i in $1 : max\_iter$ **do**
$\quad w = w + \alpha * (T^{\intercal}(Y/(1 + \exp(Tw))))$
end

Towards Linear Algebra over Normalized Data. **VLDB 2017**

MORPHEUS: High-level Architecture

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MORPHEUS

Rewrite Rules for
Factorized LA ops
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R Oracle R Enterprise NumPy TensorFlow

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ML algorithm expressed using LA ops on an LA tool

→

MORPHEUS

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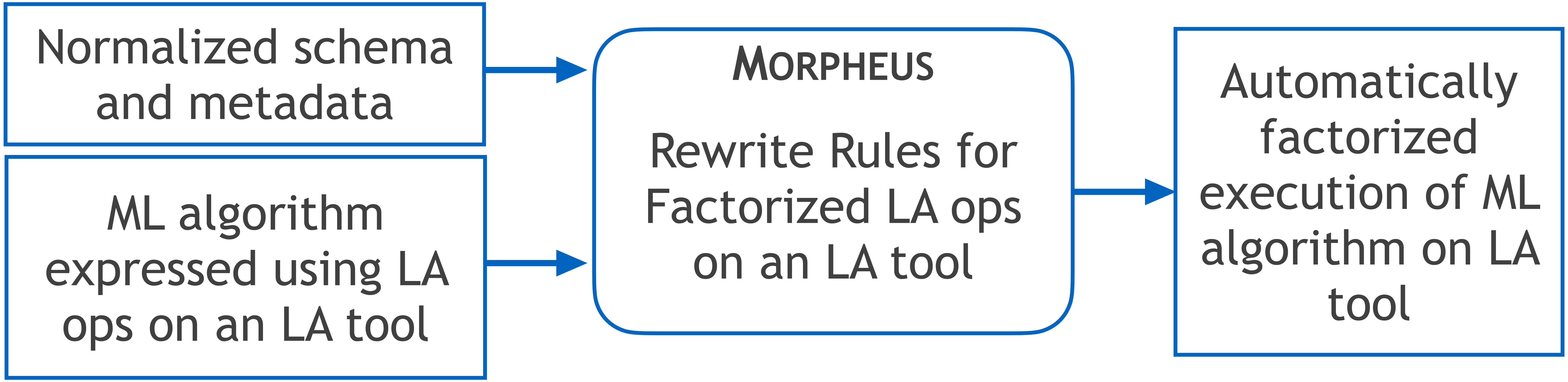

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Automatically factorized execution of ML algorithm on LA tool

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MORPHEUS: Factorized LA Rewrite Rules

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New Abstraction: "Normalized Matrix" to represent join in LA

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Framework of algebraic rewrite rules for many LA operations

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Left Matrix Multiplication:

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Automatically Factorized ML in MORPHEUS

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Input: Normalized matrix (S, K, R), Y, w, α
for i *in* $1 : max\_iter$ **do**
$\quad P = (Y/(1 + \exp(Sw[1 : d_S,]+ K(Rw[d_S + 1 : d_S + d_R,]))))^{\intercal}$
$\quad w = w + \alpha * [PS, (PK)R]^{\intercal}$
end

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LA Operations Factorized in MORPHEUS

Table 1: Operators and functions of linear algebra handled in this paper over a normalized matrix T.

Op Type	Name	Expression	Output Type	Parameter X or x	Factorizable
Element-wise Scalar Op	Arithmetic Op ($\oslash = +, -, *, /, \hat{}$, etc)	$T \oslash x$ or $x \oslash T$	Normalized Matrix	A scalar	Yes
	Transpose	$T^{\intercal}$		N/A	
	Scalar Function f (e.g., log, exp, sin)	$f(T)$		Parameters for f	
Aggregation	Row Summation	rowSums(T)	Column Vector	N/A	
	Column Summation	colSums(T)	Row Vector		
	Summation	sum(T)	Scalar		
Multiplication	Left Multiplication	TX	Regular Matrix	$(d_S + d_R) \times d_X$ matrix	
	Right Multiplication	XT		$n_X \times n_S$ matrix	
	Cross-product	crossprod(T)		N/A	
Inversion	Pseudoinverse	ginv(T)			
Element-wise Matrix Op	Arithmetic Op ($\oslash = +, -, *, /, \hat{}$, etc)	$X \oslash T$ or $T \oslash X$		$n_S \times (d_S + d_R)$ matrix	No

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Snapshot of Empirical Results

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Prototype in R (and Python) for listed LA ops; ~800 LOC; commodity machine

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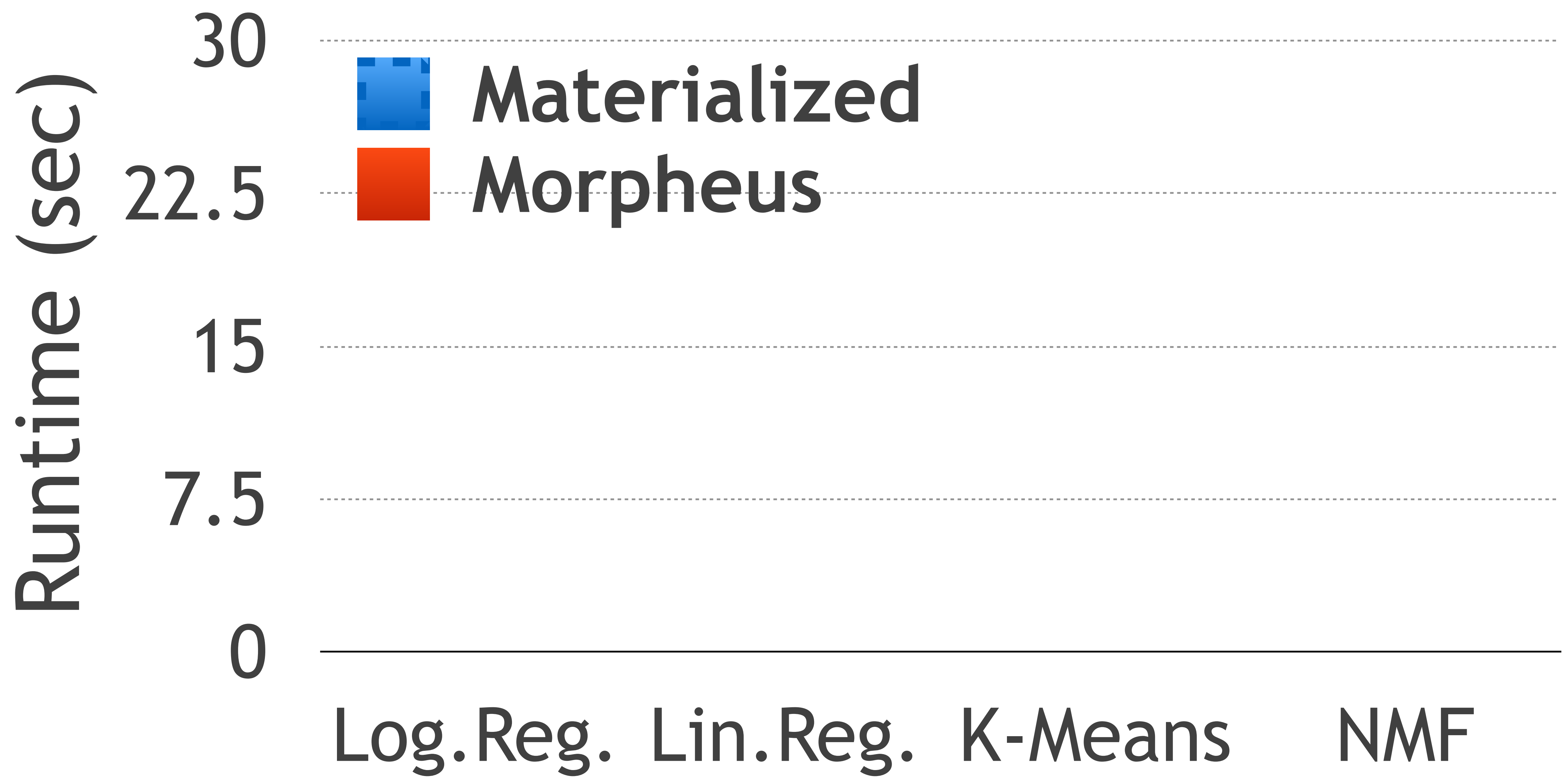

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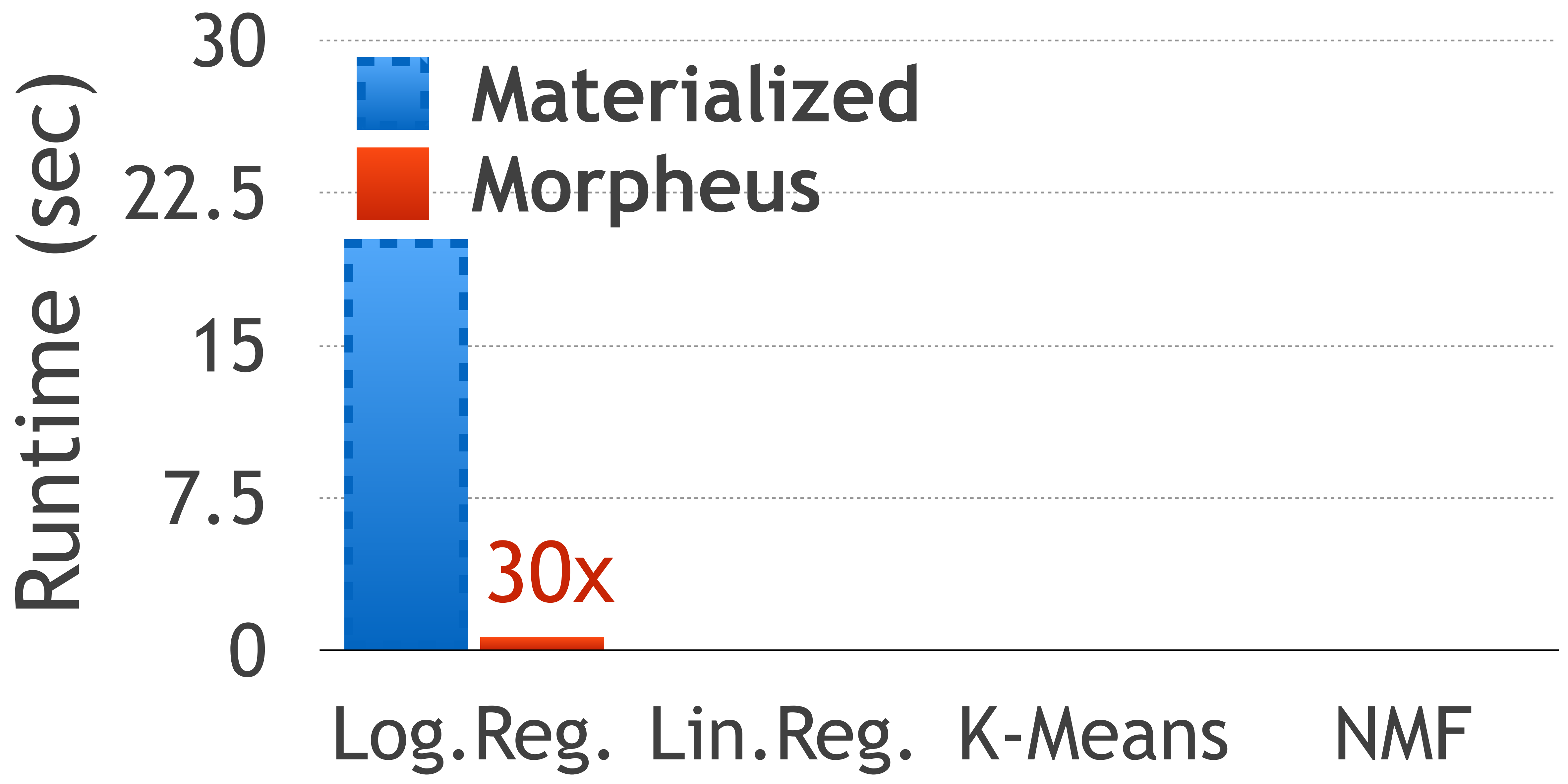

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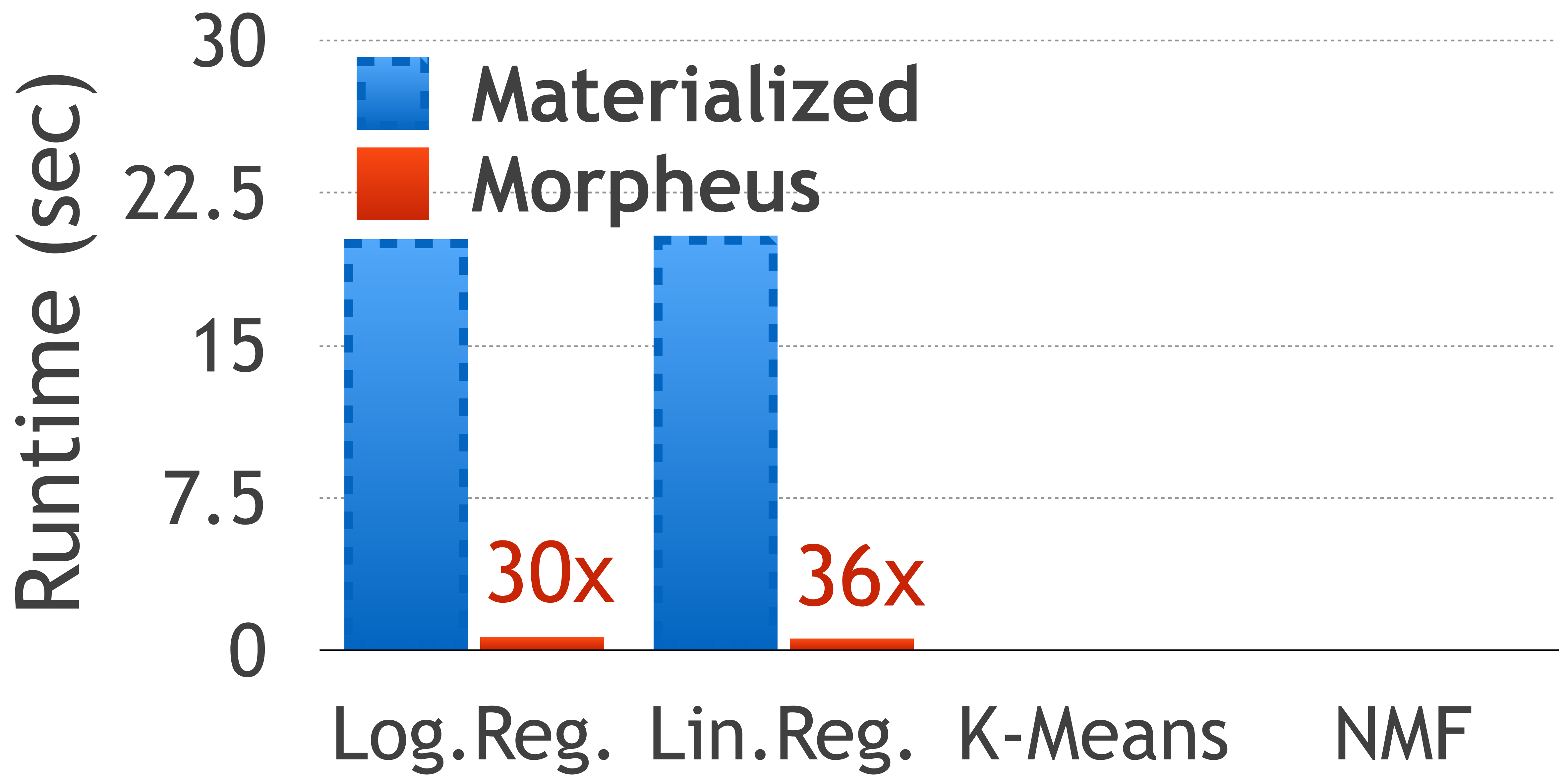

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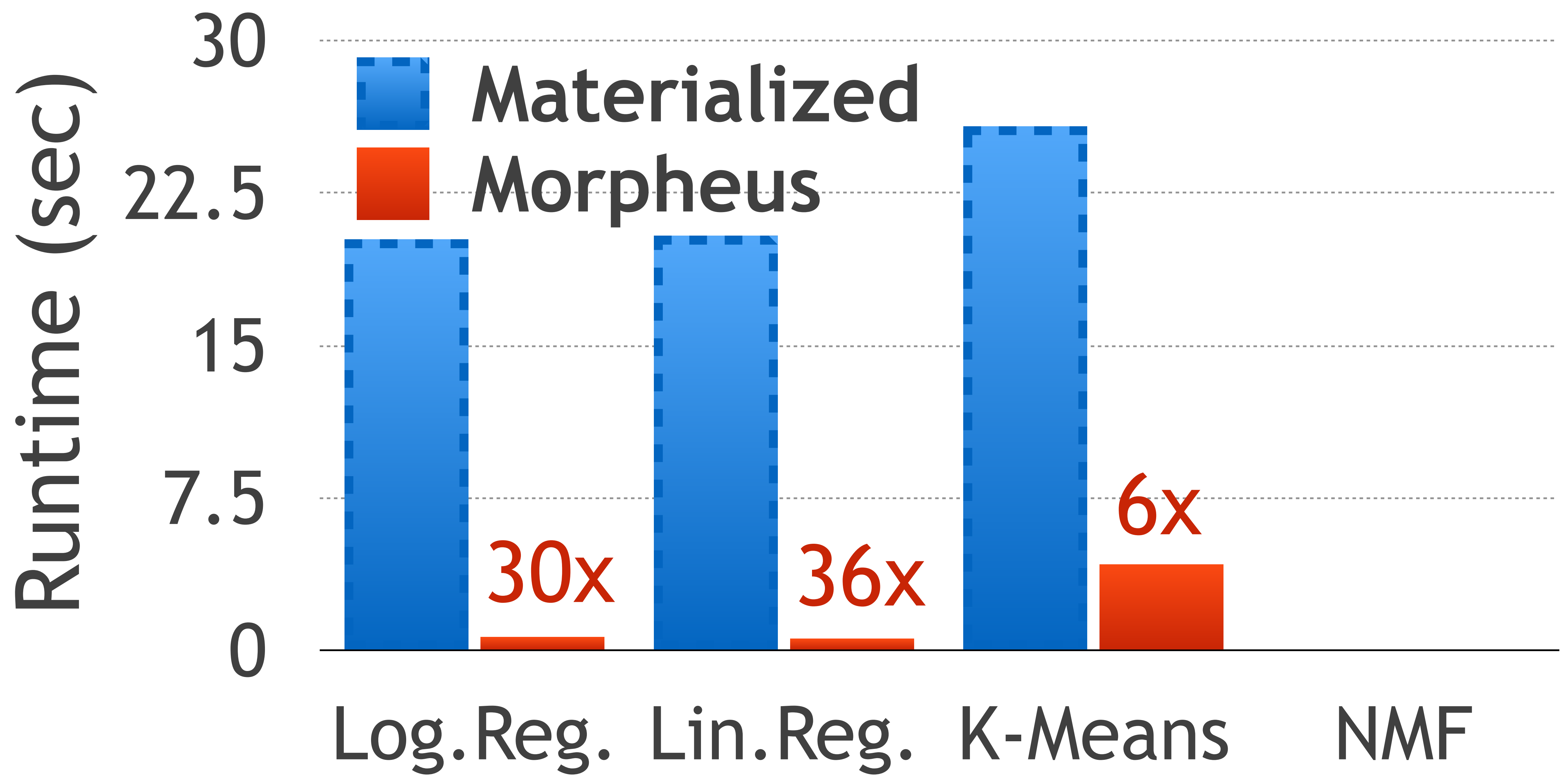

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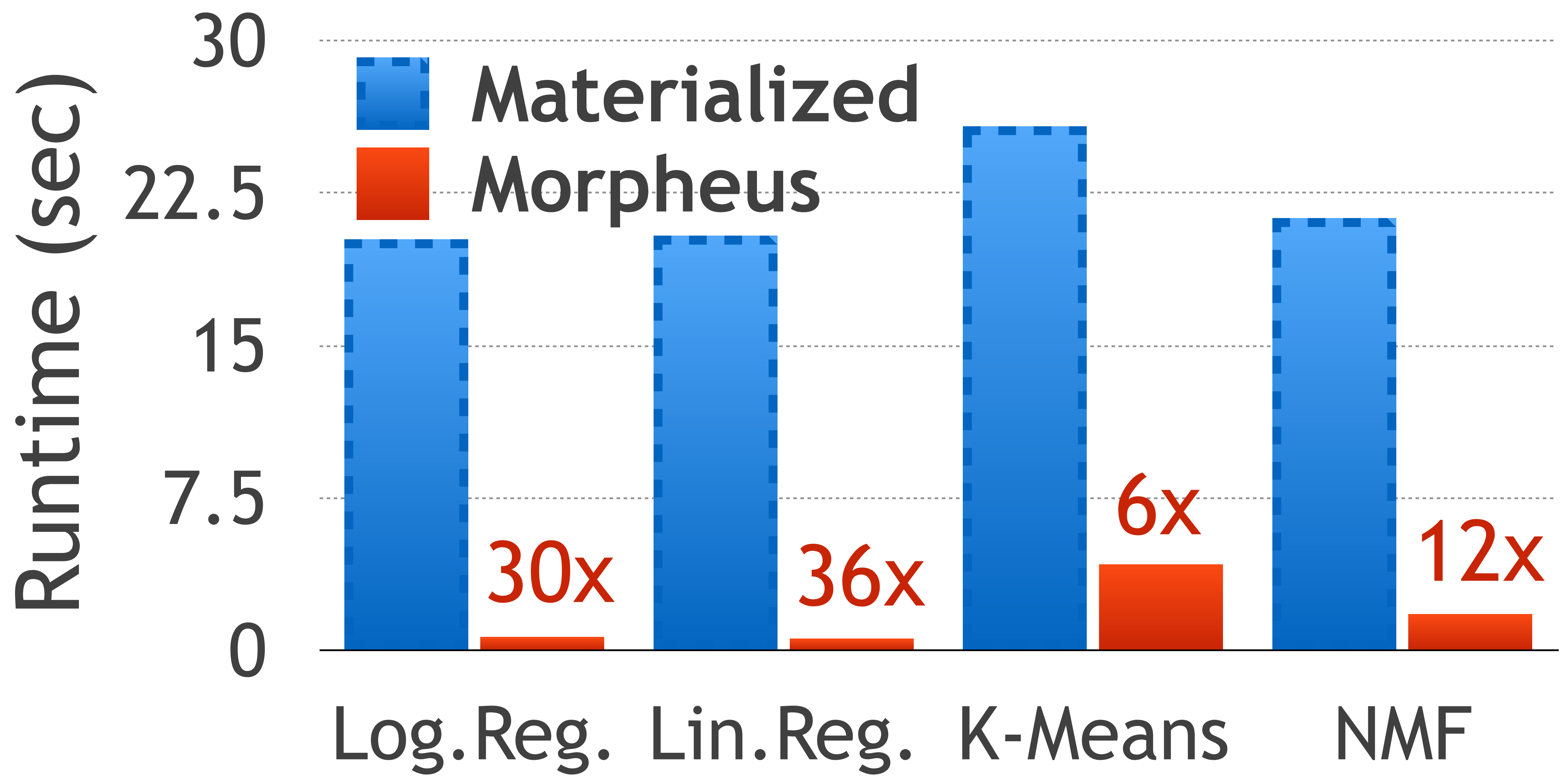

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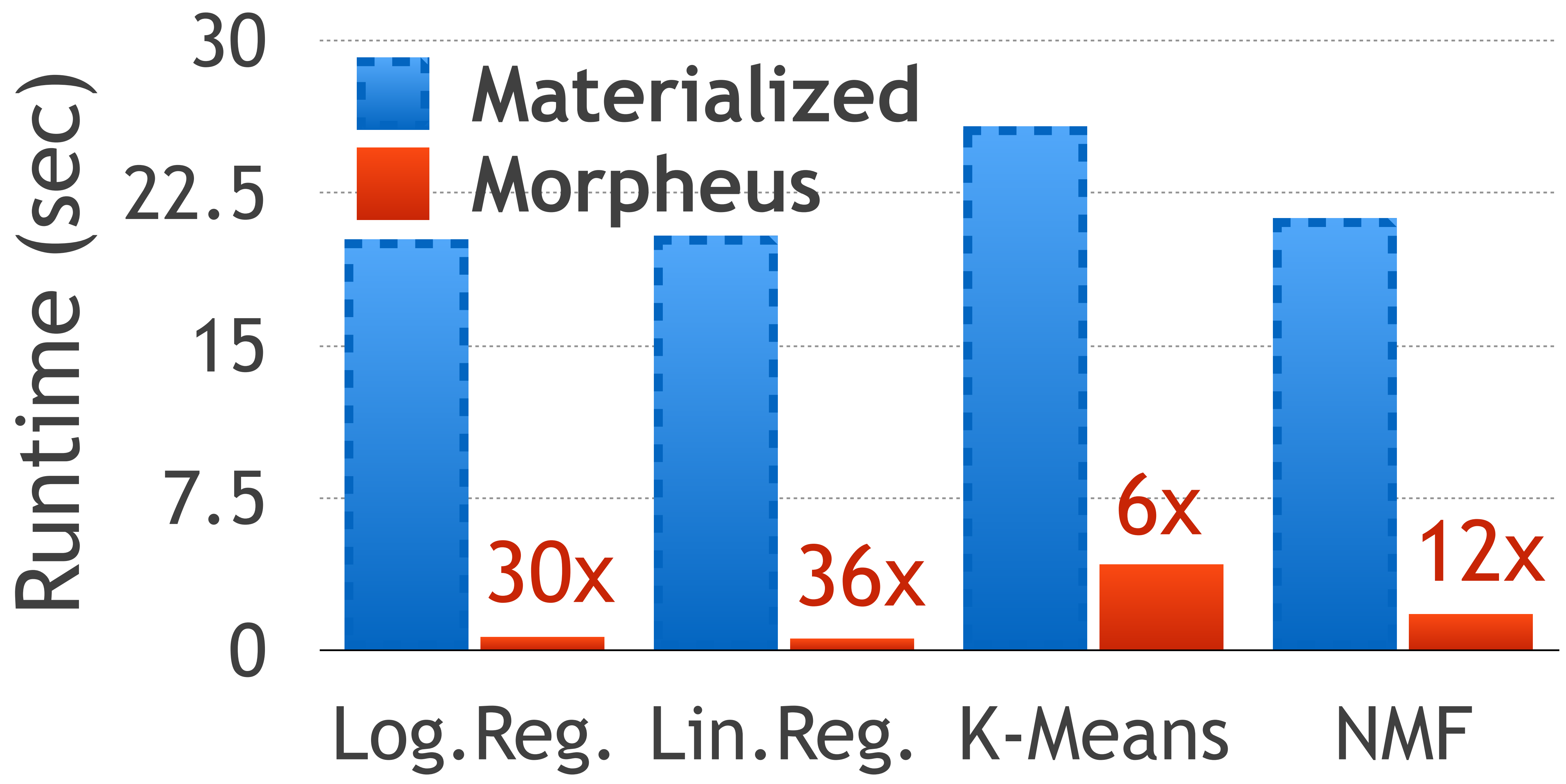

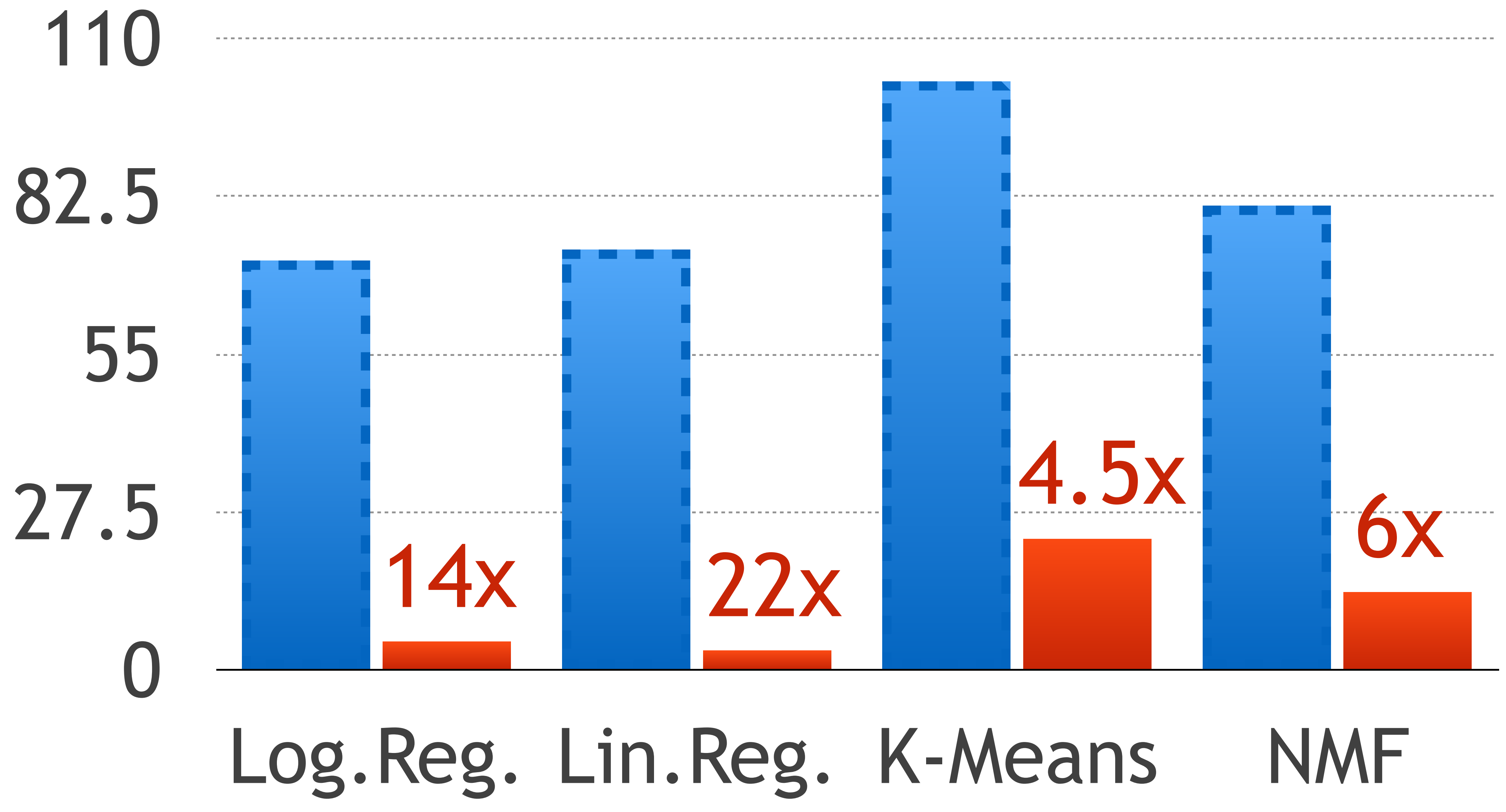

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When is MORPHEUS not likely to be beneficial?

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Short Answer: When the join(s) do *not* introduce much redundancy

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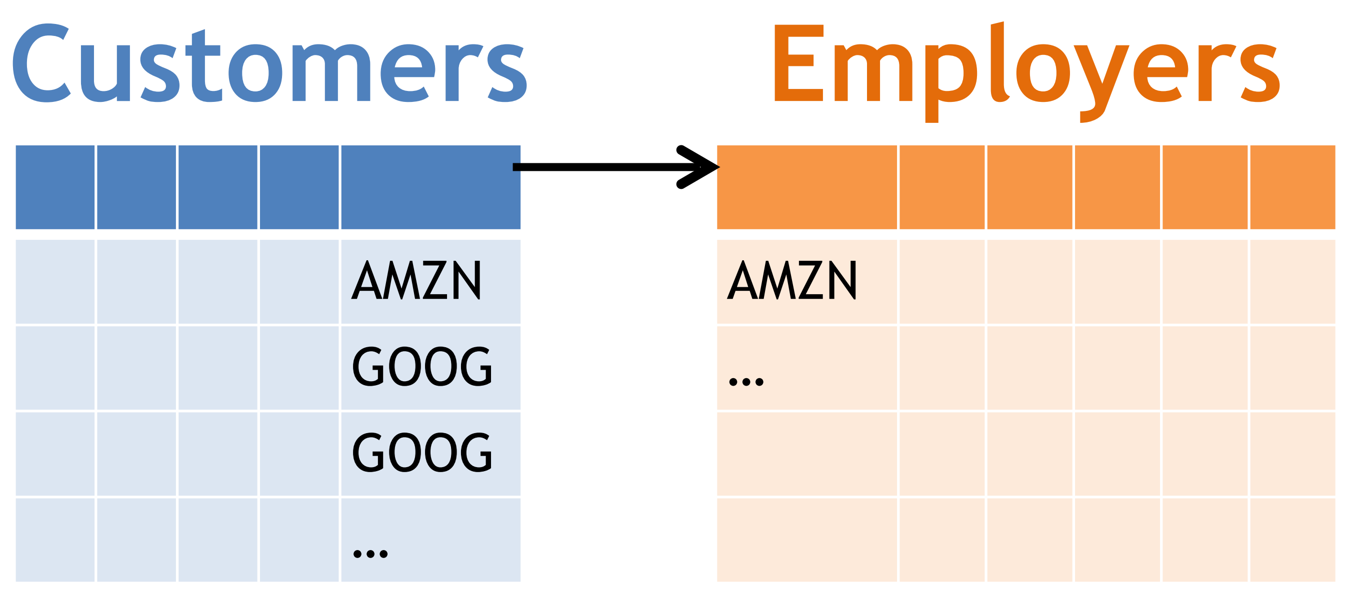
Case 1:

Fact table is *not much taller* than dimension table(s)



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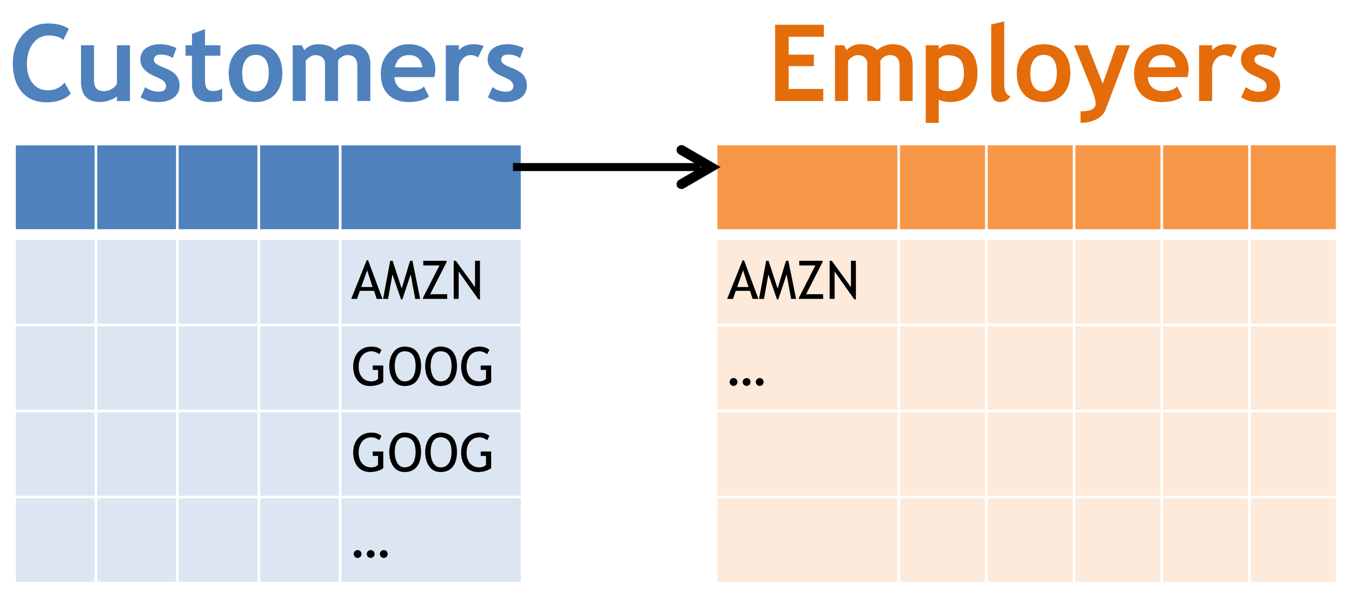
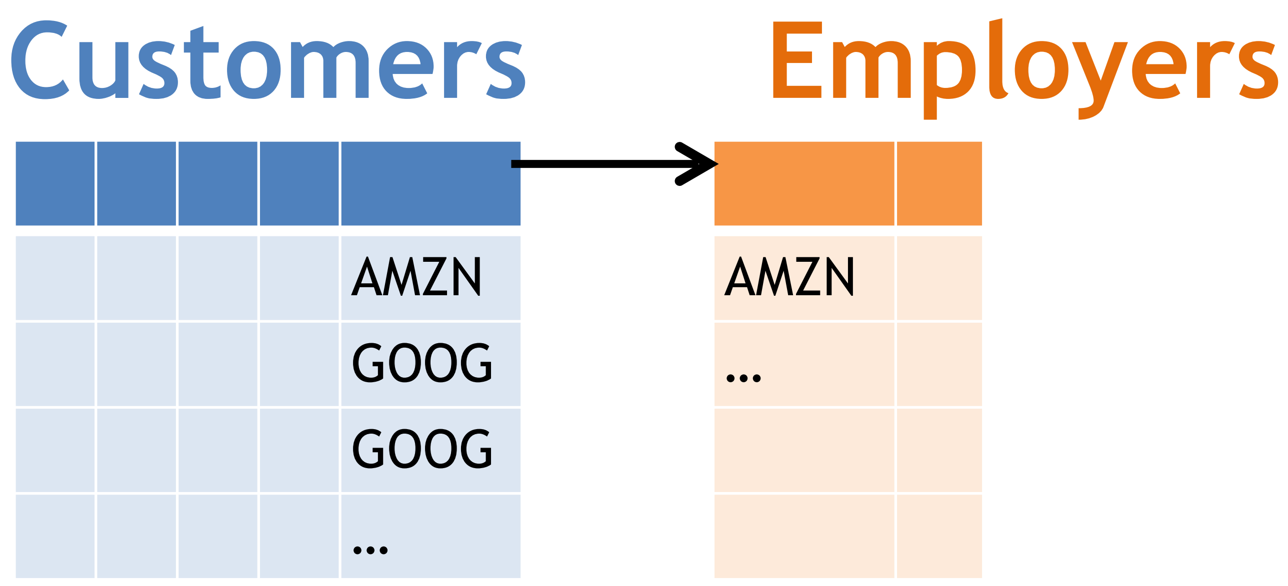


Case 2:
Dimension table has *much fewer* features than fact table



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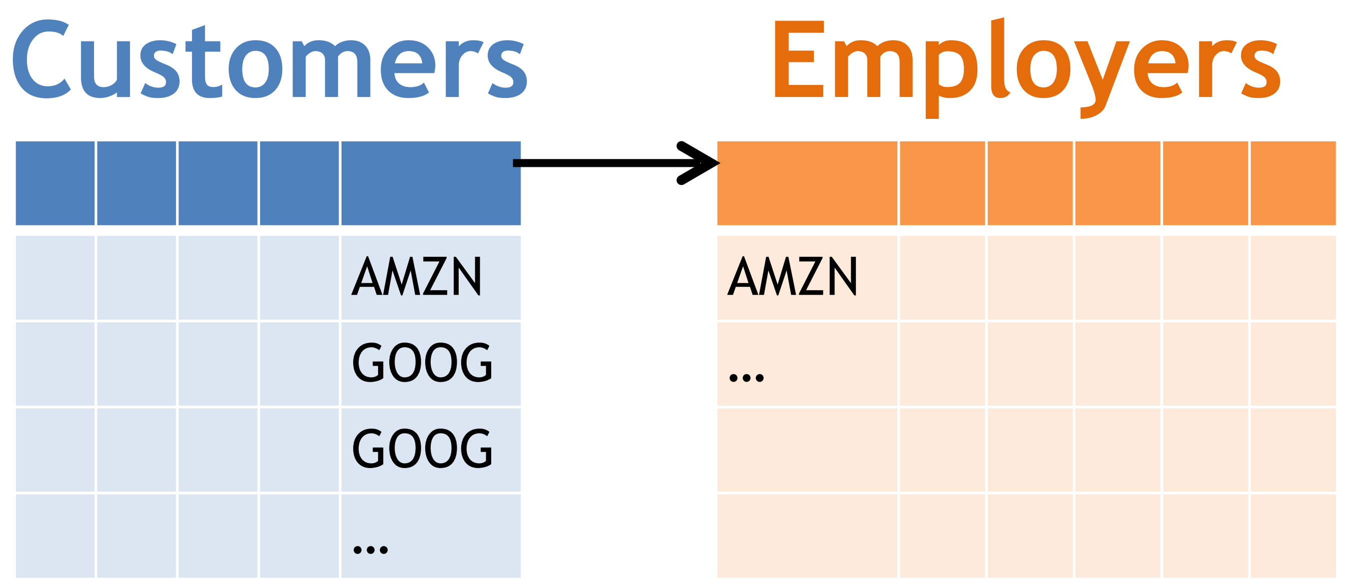

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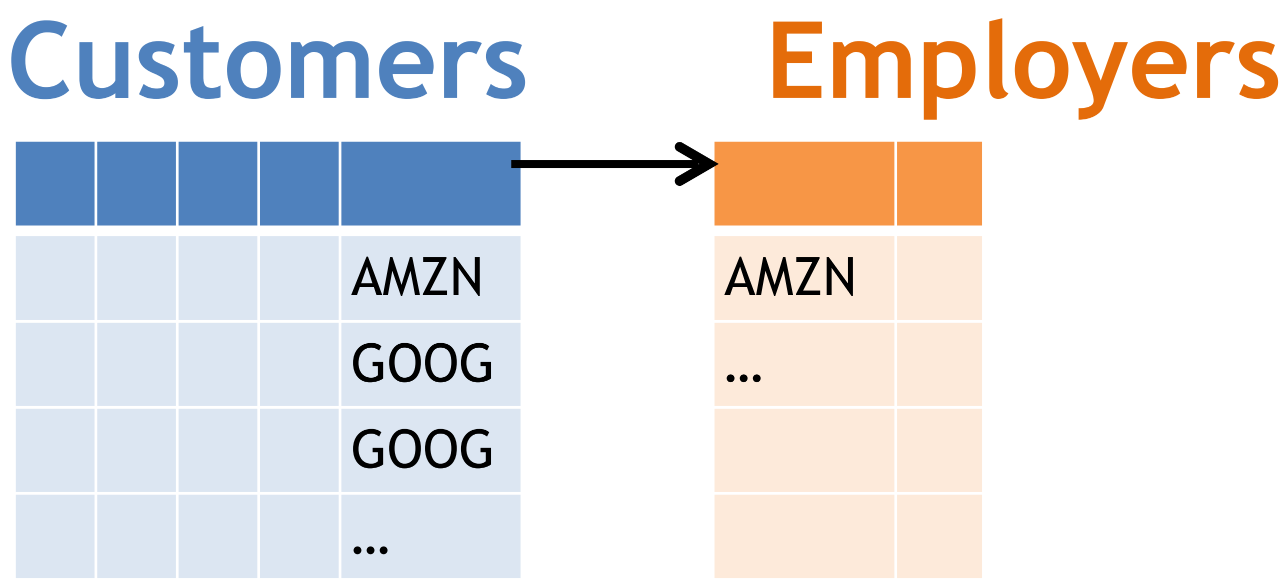

Case 3: MLPs do *not* have much computational redundancy (anyway)

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MORPHEUS: Implementations and Extensions

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Avito Google ORACLE

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TOC: Generalized data compression for SGD

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TRINITY: MORPHEUS Meets Oracle GraalVM

Towards A Polyglot Framework for Factorized ML. **VLDB 2021**

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Goal: *Automate* Morpheus itself to many PLs in a unified way

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Idea: Exploit GraalVM, an industrial-strength *polyglot* compiler + runtime for data science workloads (R, Py, Javascript, etc.)

Towards A Polyglot Framework for Factorized ML. **VLDB 2021**

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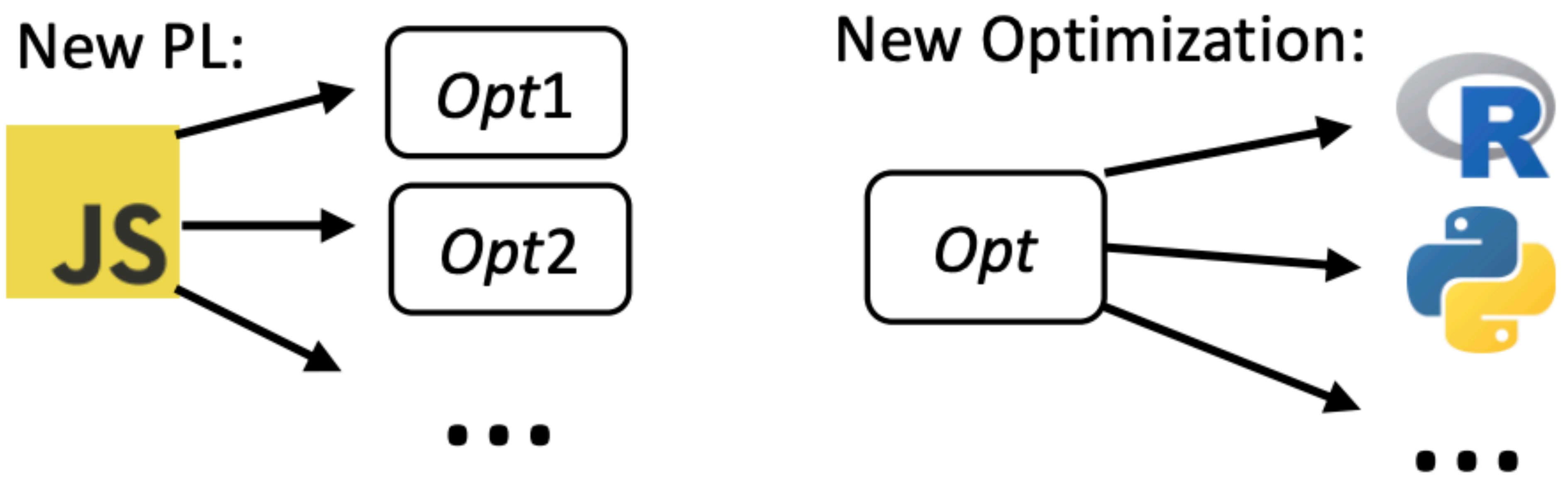
Idea: Exploit GraalVM, an industrial-strength *polyglot* compiler + runtime for data science workloads (R, Py, Javascript, etc.)

World without Trinity



Towards A Polyglot Framework for Factorized ML. **VLDB 2021**

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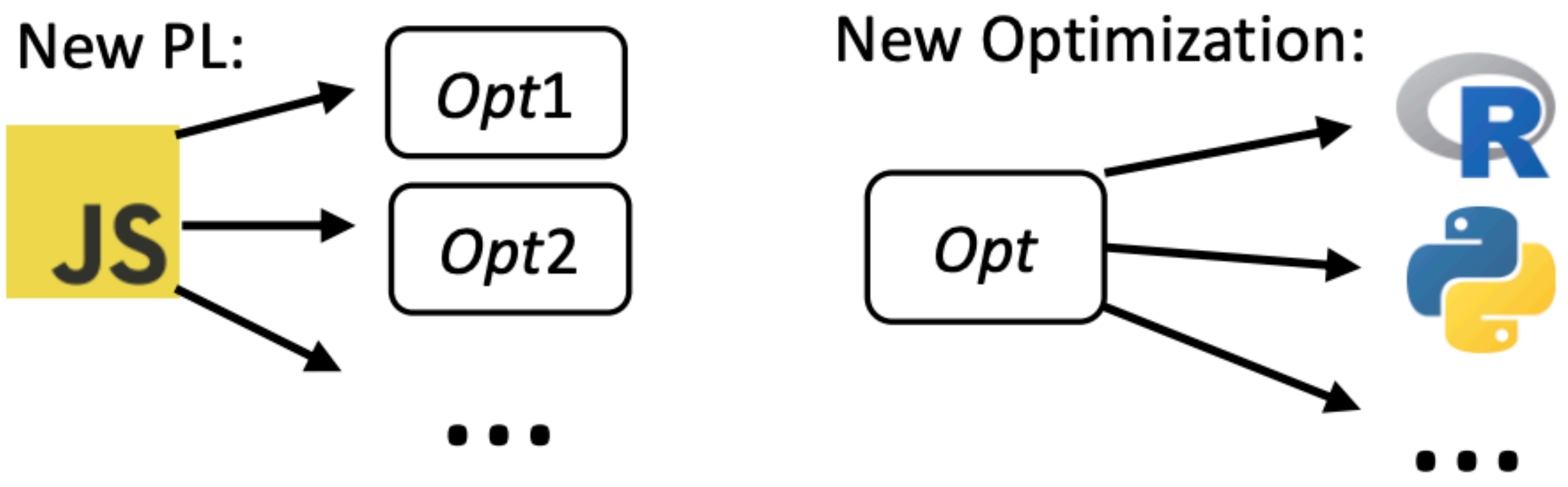

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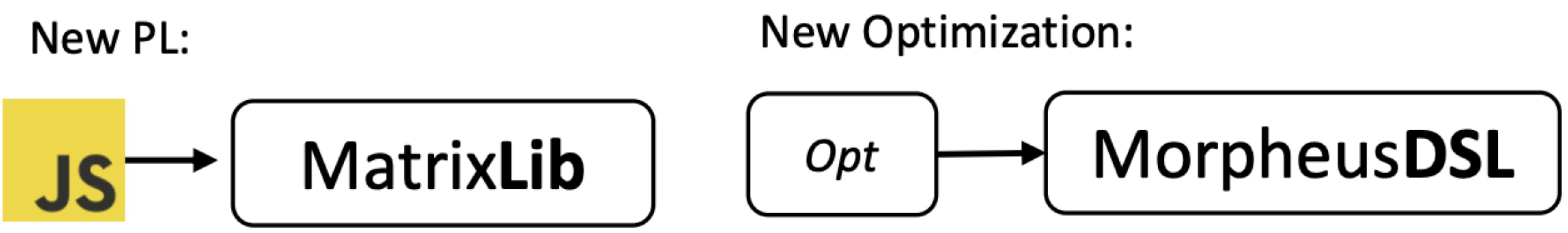

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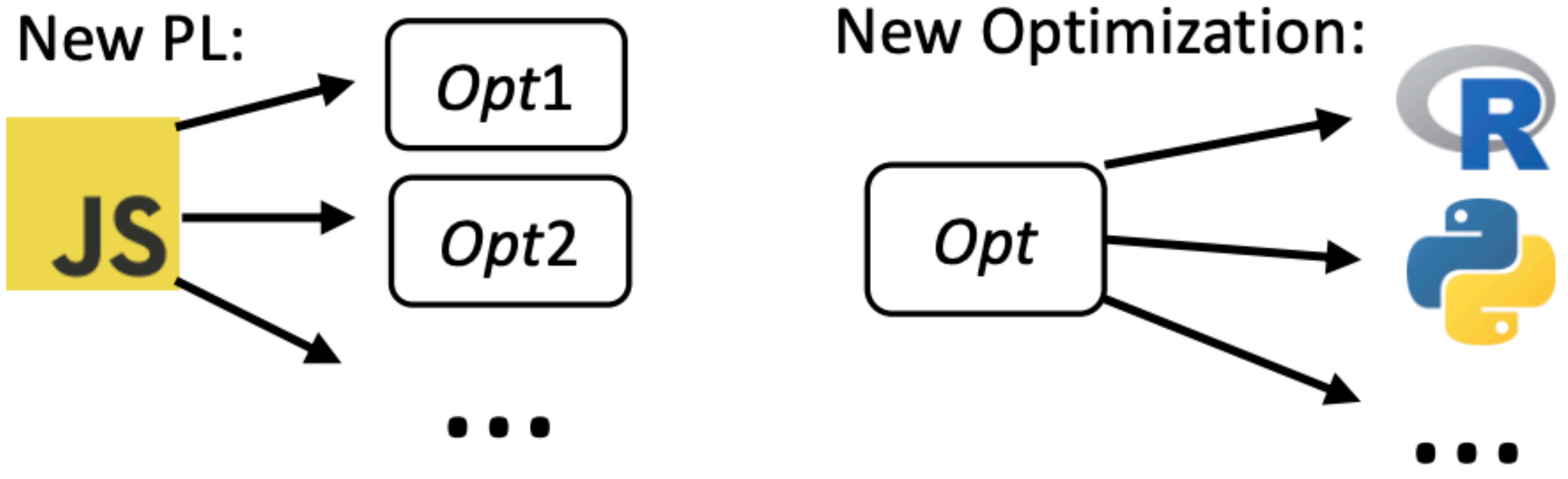

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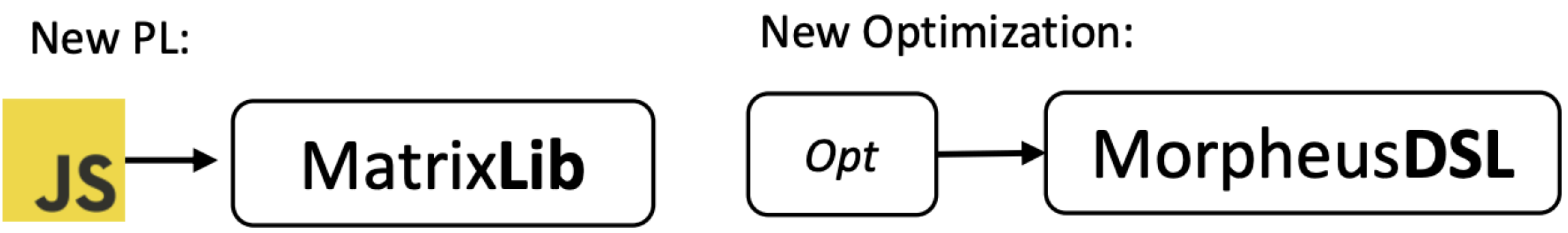
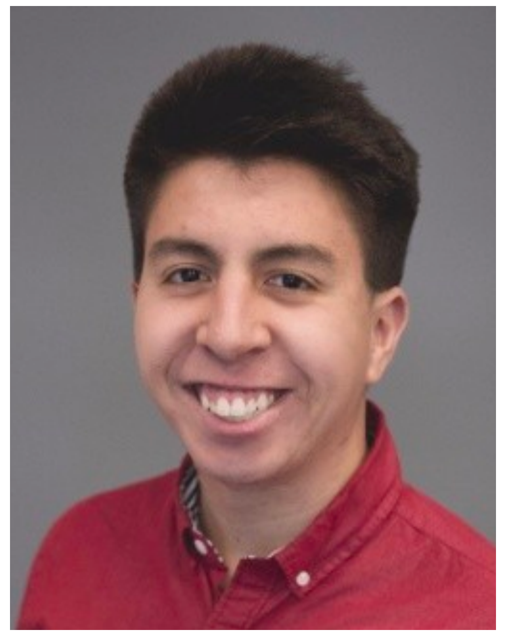


Learn more about Trinity from David Justo at 3:30pm today!



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Outline

4m Introducing ML over Joins

4m Orion: Factorized ML

10m Morpheus and Extensions

4m Roadblocks and Musings

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Reason 2: *Implementation* effort to make it practical still non-trivial

Orion-style: UDFs too complex to implement/maintain on RDBMS/Spark

Morpheus-style: ML not always written as LA scripts; hidden C++ callouts

Trinity-style: Likely promising; over the wall at Oracle now! :)

Plug: First Textbook on ML Systems

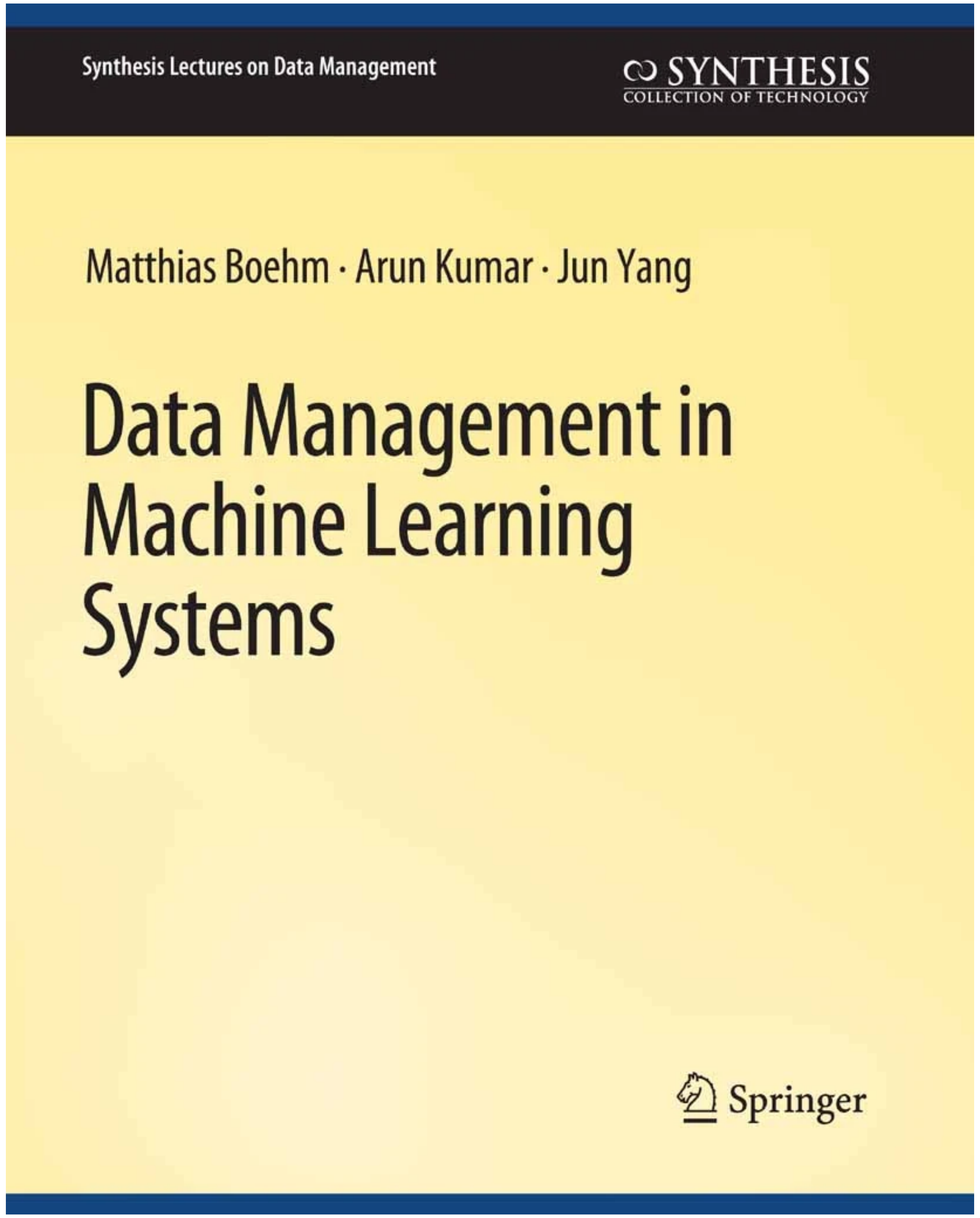

Table of Contents

https://tinyurl.com/MLSystemsBook

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