

MLSQL: Machine Learning Meets SQL

V. Chakraborty and G. Muktadir

Introductio

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MLSQL

Syntax

Design

Novelt

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Outline

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Design Choices

- 1 Introduction
- 2 MLSQL
- 3 Syntax
- 4 Design Choices
- 5 Novelty



Motivation

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Objective

- A vast amount of data around us these days (the usual Big Data spiel!)
- Machine Learning, a lot like the President's impeachment
 - Everyone is excited about it
 - Everyone is talking about it
 - No one (very few) is really doing it!
- Popularity of SQL extremely commonplace

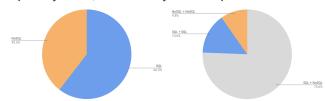


Figure: Prevalence of SQL Databses



Motivation

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- Subjective
 - Python extremely popular, host of libraries
 - SQLite
 - Portability
 - Throughput
 - Popularity
 - Popularity of SQL extremely commonplace



Figure: SQLite usage in industry



Motivation

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- What we found helpful?
 - Theoretical foundation of Relation DB model long tested and still popular
 - Experience with
 - Tenserflow
 - Scikit Learn
 - SQL and no SQL databases
 - Pytorch
 - Theano
 - Data Analysis
 - Machine Learning
 - Distributed Systems



Overview

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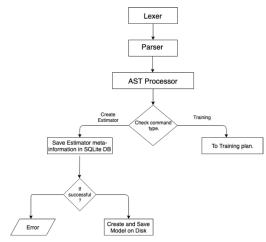


Figure 2: Execution flow in MLSQL

Figure: MLSQL



Overview Training

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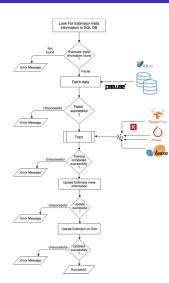


Figure: Flow to train in MLSQL



Example Linear Regression

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Create a model

CREATE ESTIMATOR salaryPred
TYPE LR FORMULA \$salary~years~...\$;

- attributes in FORMULA must be names of columns in tables of the dataset that will be used.
- Create a training profile
 CREATE TRAINING PROFILE salaryProfile
 WITH [SELECT * FROM salary];
- Select the database USE 'data/salarydb.db';
- Training an estimator with a training profile TRAIN salaryPred WITH TRAINING PROFILE salaryProfile;

Syntax "Grammar Rule"

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Estimator



Figure: Estimator Attributes

■ Training Profile

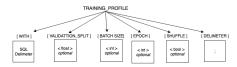


Figure: Training Profile Attributes



So what's happening?

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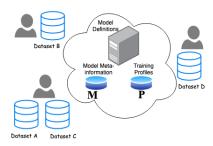


Figure: MLSQL - Overview

- Create model. Store meta-information in database *M* and the actual model to disk.
- Create training profile. Store profile in database *P*.
- Use a model from *M* with profile from *P* on a dataset of the client's choice.



A Specific Design Choice Where to place the model/estimator?

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■ Two alternatives

- Place the model inside the database
 - Better portability
- Place it outside the database
 - Better reusability
 - Use the same model on different datasets/databases
 - Share the same model
 - Replicate model for production
- We place it outside the database
 - We foresee a setting in which MLSQL is used to create a model and used with different data-sets.
 - Trade portability for reusability
 - Training Profile can be created by a domain expert. But the dataset can be changed by someone who is not.



Other Design Choices

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Why SQL?

- Recent progress Tensor Flow API for javascript users
- We are providing ML to SQL users

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- Next... ML for HTML and IATEX users !!
- SQLite3 and Pewee ORM
 - "virtual object database" that can be used from within the programming language



Is this idea completely new?

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- Surely not! However, ours is pretty dope
 - opensource
 - No "new" language
 - Abstracts using ML into two steps
 - Model Engineering (for trained experts)
 - Model Implementation (for everyone)
 - Try to minimise "shoot-in-the-dark" trend of machine learning.
- Here are some tools that inspired us...
 - Uber's Queryparser [1]
 - no ML but helped us conceive the design of our parser
 - Google's BigQuery [2] used in conjunction with MapReduce
 - serverless service
 - complicated code
 - expensive



Novelty Continued...

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Design Choice:

Novelty

■ Microsoft's SQL Server 2017 [3]

- separate core language which is quite different from other DB applications
- expensive
- companies that want to upgrade need to teach current employees how to work with the application
- .NET framework dependent



Bibliography I

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Appendix
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Thank you!