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Bachelor Thesis

My Bachelor Thesis

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Eidesstattliche Erklärung

Ich versichere hiermit, dass ich, Marcel Pascal Stolin, die vorliegende Bachelor Thesis selbstständig angefertigt, keine anderen als die angegebenen Hilfsmittel benutzt und sowohl wörtliche als auch sinngemäß entlehnte Stellen als solche kenntlich gemacht habe. Die Arbeit hat in gleicher oder ähnlicher Form noch keiner anderen Prüfungsbehörde vorgelegen.

Ort, Datum: ___________________________

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Marcel Pascal Stolin

Zusammenfassung

Hier kommt eine deutschsprachige Zusammenfassung hin.

Abstract

Abstract in English.

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Notation

Konventionen

x	Skalar
$\underline{x}$	Spaltenvektor
$\boldsymbol{x}, \underline{\boldsymbol{x}}$	Zufallsvariable/-vektor
$\hat{x}, \hat{\underline{x}}$	Mittelwert/-vektor
$x^*, \underline{x}^*$	Optimaler Wert/Vektor
$x_{0:k}, \underline{x}_{0:k}$	Folge von Werten $(x_0, x_1, \ldots, x_k)$ / Vektoren $(\underline{x}_0, \underline{x}_1, \ldots, \underline{x}_k)$
$\mathbf{A}$	Matrizen
$\mathcal{A}$	Mengen
$\preceq, \prec$	schwache/strenge Präferenzrelation
$\mathbb{R}$	Reelle Zahlen
$\mathbb{N}$	Natürliche Zahlen
$\blacksquare$	Ende eines Beispiels
$\square$	Ende eines Beweises

Operatoren

$\mathbf{A}^{\mathrm{T}}$	Matrixtransposition
$\mathbf{A}^{-1}$	Matrixinversion
$\lvert\mathbf{A}\rvert$	Determinante einer Matrix
$\lvert\mathcal{A}\rvert$	Kardinalität der Menge $\mathcal{A}$
$\mathrm{pot}(\mathcal{A})$	Potenzmenge von $\mathcal{A}$
$\mathrm{E}\{\cdot\}$	Erwartungswertoperator
$\mathcal{O}(g)$	O-Kalkül entsprechend der Landau-Notation bei welcher beispielsweise $f(x) \in \mathcal{O}(g(x))$ besagt, dass die Funktion $f(x)$ die Komplexität $\mathcal{O}(g(x))$ besitzt

Spezielle Funktionen

$\Pr(\mathcal{E})$	Wahrscheinlichkeitsmaß, welches die Wahrscheinlichkeit angibt, dass Ereignis $\mathcal{E}$ eintritt
$p(\underline{x})$	(Wahrscheinlichkeits-)Dichtefunktion für kontinuierliche $\underline{x}$

	und Zähldichte für diskrete $\underline{x}$
$p(\underline{x}\|\underline{y})$	Bedingte Dichtefunktion
$P(\underline{x})$	(Wahrscheinlichkeits-)Verteilungsfunktion
$\mathrm{erf}(x)$	Gauß'sche Fehlerfunktion
$\exp(x)$	Exponentialfunktion e^x
$\mathcal{N}(\underline{x}; \hat{\underline{x}}, \mathbf{C}_x)$	Gaußdichte, d. h. Dichtefunktion eines normalverteilten Zufallsvektors $\underline{\boldsymbol{x}}$ mit Mittelwertvektor $\hat{\underline{x}}$ und Kovarianzmatrix $\mathbf{C}_x$

Kapitel 1

Introduction

Storing huge amounts of data has become inexpensive in recent years, but processing it, requires parallel computations on clusters with multiple machines [CZ18]. Complex computation operations rely on a IT infrastructure with the ability to perform operations on scale.

In order to achieve high scalability, computing systems need to adapt dynamically to demands and conditions of the workload.

1.1 Problem statement

ETL [1] operations are compute-intensive. During the execution of analytic applications, performance thresholds can be reached and the computing system can become out-of-order.

In addition, many algorithms profit from data-parallelism.

1.2 Research questions

1.3 Thesis structure

1 Extract transform load

Kapitel 2

Related Work

Kapitel 3

Background

In this chapter bla bla

3.1 Autonomic computing

Autonomic computing is an architecture for computing systems to enable the ability to manage themselves in accordance to high level objectives configured by administrators [KC03]. These computing systems dynamically adapt to demands and conditions of the workload [KC03]. An intelligent control-loop is responsible to collect all important details of the computing system and make decision according to the collected details. To automate the tasks, the intelligent control-loop is organized into four categories:

- **Self-configuring** - Components in the environment have to adapt dynamically to system changes using policies. For example, deploying or removing new components.
- **Self-healing** - If system errors have being detected, the control-loop has to perform policy-based actions without disrupting the environment.
- **Self-optimizing** - The control-loop has to monitor the resources and should adapt to changes dynamically.
- **Self-protecting** - Detection and protection against threats.

An autonomic computing environment consists of an autonomic manager, managed-resources and a knowledge-base.

3.1.1 Managed resources

Managed resources are software or hardware components in the computing environment. For example, a managed resource can be a database, service, application, server or different entity. Each managed resource implements an interface to enable the autonomic manager to communicate with the managed resource.

These interface are called touchpoints.

3.1.2 Autonomic manager

The autonomic manager implements an intelligent control-loop to collect system metrics from the managed resources and acts according to the collected details. It can only make adjustments within it‘s own scope and uses policies to make decisions of what actions have to be executed to accommodate the objectives. To be self-managing, the autonomic manager has to implement the following four automated functions.

- **Monitor** - The monitor function is responsible to collect the needed metrics from all managed resources and applies aggregation and filter operations to the collected data. After that the function reports the metrics.
- **Analyze** - To determine if changes have to be made to the computing system, the collected data has to be analyzed.
- **Plan** - If changes have to be made, an appropriate change plan has to be generated. A change plan consists of actions that are needed to achieve the configured goals and objectives. The change plan needs to be forwarded to the execute function.
- **Execute** - The execute function applies all necessary changes to the computing system.

Multiple autonomic manager can exist in an autonomic computing environment to perform only certain parts. For example, there can be one autonomic manager which is responsible to monitor and analyze the system and another autonomic manager to plan and execute. To create a complete and closed control-loop, multiple autonomic manager can be composed together.

3.2 Docker

3.3 Apache Spark

Apache Spark is an open-source computing framework for parallel data processing on a large computer cluster. Spark manages the available resources and distributes computation tasks across a cluster to perform big-data processing operations at large scale [CZ18]. Before Spark was developed, Hadoop MapReduce [DG10] was the framework of choice for parallel operations on a computer cluster [ZCF$^+$10]. Spark accomplished to outperform Hadoop by

10x for iterative Machine Learning [ZCF+10]. It is implemented in Scala[1], a JVM-based language and provides a programming interface for Scala, Java[2], Python[3] and R[4]. In addition, Spark includes an interactive SQL shell and libraries to implement Machine Learning and streaming applications [CZ18]. It was developed in 2009 as the Spark research project at UC Berkeley and became an Apache Software Foundation project in 2013 [CZ18].

3.3.1 Spark programming model

Spark provides resilient distributed datasets (RDDs) as the main abstraction for parallel operations [ZCF+10]. Core types of Spark‘s higher-level structured API are built on top of RDDs [CZ18] and will automatically optimized by Spark‘s Catalyst optimizer to run operations quick and efficient [Luu18].

Resilient distributed datasets: Resilient distributed datasets are fault-tolerant, parallel data structures to enable data sharing across cluster applications [ZCD+12]. They allow to express different cluster programming models like MapReduce, SQL and batched stream processing [ZCD+12]. RDDs have been implemented in Spark and serve as the underlying data structure for higher level APIs (Spark structured API) [ZCD+12]. RDD‘s are a immutable, partitioned collection of records and can only be initiated through transformations (e.g. map, filter) on data or other RDD‘s. An advantage of RDDs is, that they can be recovered through lineage. Lost partitions of an RDD can be recomputed from other RDDs in parallel on different nodes [ZCD+12]. RDDs are lower level APIs and should only be used in applications if custom data partitioning is needed [CZ18]. It is recommended to use Sparks structured API objects instead. Optimizations for RDDs have to be implemented manually while Spark automatically optimize the execution for structured API operations [CZ18].

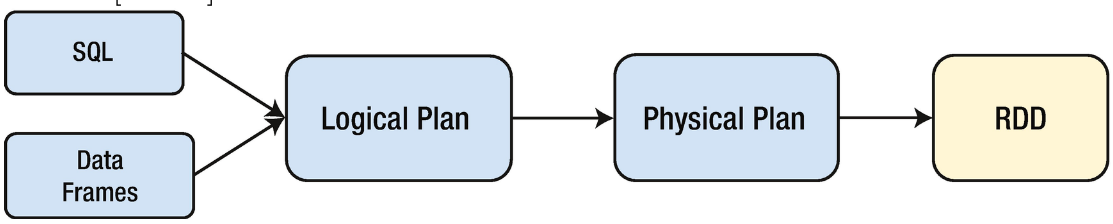
Spark structured API: Spark provides high level structured APIs for manipulating all kinds of data. The three distributed core types are Datasets, DataFrames and SQL Tables and Views [CZ18]. Datasets and DataFrames are immutable, lazy evaluated collections that provide execution plans for operations [CZ18]. SQL Tables and Views work the same way as DataFrames, except that SQL is used as the interface instead of using the DataFrame programming interface [CZ18]. Datasets use JVM types and are therefore only available for JVM based languages. DataFrames are Datasets of type Row, which is the Spark internal optimized format for computations. This has advantages over JVM types which comes with garbage collection and object instantiation [CZ18].

1 Scala programming language. https://www.scala-lang.org/
2 Java programming language. https://www.oracle.com/java/
3 Python programming language. https://www.python.org/
4 R programming language. https://www.r-project.org/

Spark Catalyst: Spark also provides a query optimizer engine called Spark Catalyst. The Spark Catalyst optimizer automatically optimizes Spark applications to run quickly and efficient. Before executing the user‘s code, the Catalyst optimizer translates the data-processing logic into a logical plan and optimizes the plan using heuristics [Luu18]. After that, the Catalyst optimizer converts the logical plan into a physical plan to create code that can be executed [Luu18].

Logical plans get created from a DataFrame or a SQL query. A logical plan represents the data-processing logic as a tree of operators and expressions where the Catalyst optimizer can apply sets of rule-based and cost-based optimizations [Luu18]. For example, the Catalyst can position a filter transformation in front of a join operation [Luu18].

From the logical plan, the Catalyst optimizer creates one ore more physical plans. The cheapest physical will be generated into Java bytecode for execution [Luu18].



Structured API execution

3.3.2 Cluster modes

3.3.3 Spark application implementation

3.4 Prometheus

3.5 NVIDIA RAPIDS

3.6 Gitlab CI/CD

3.7 K-MEANS

3.8 Naive Bayes Classifier

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