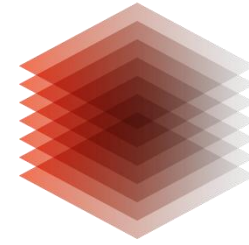

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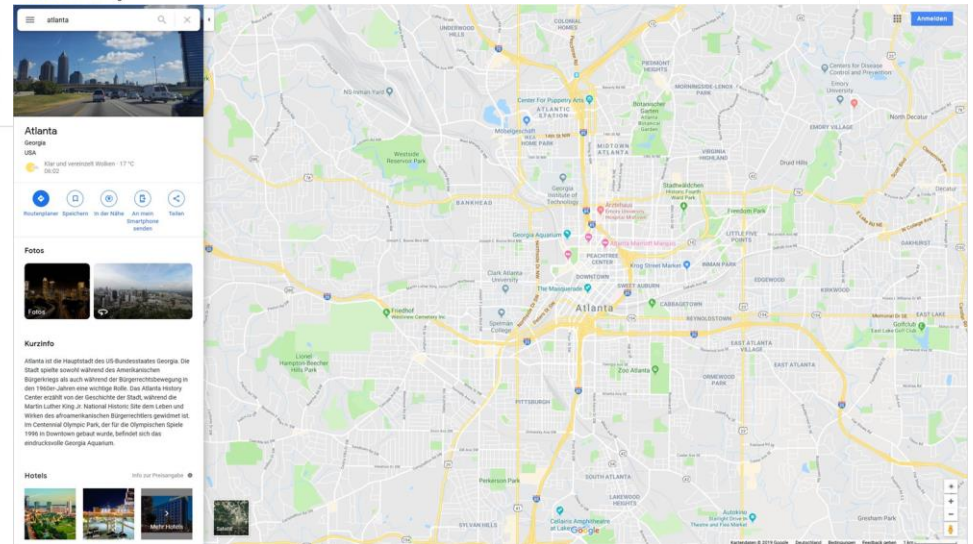
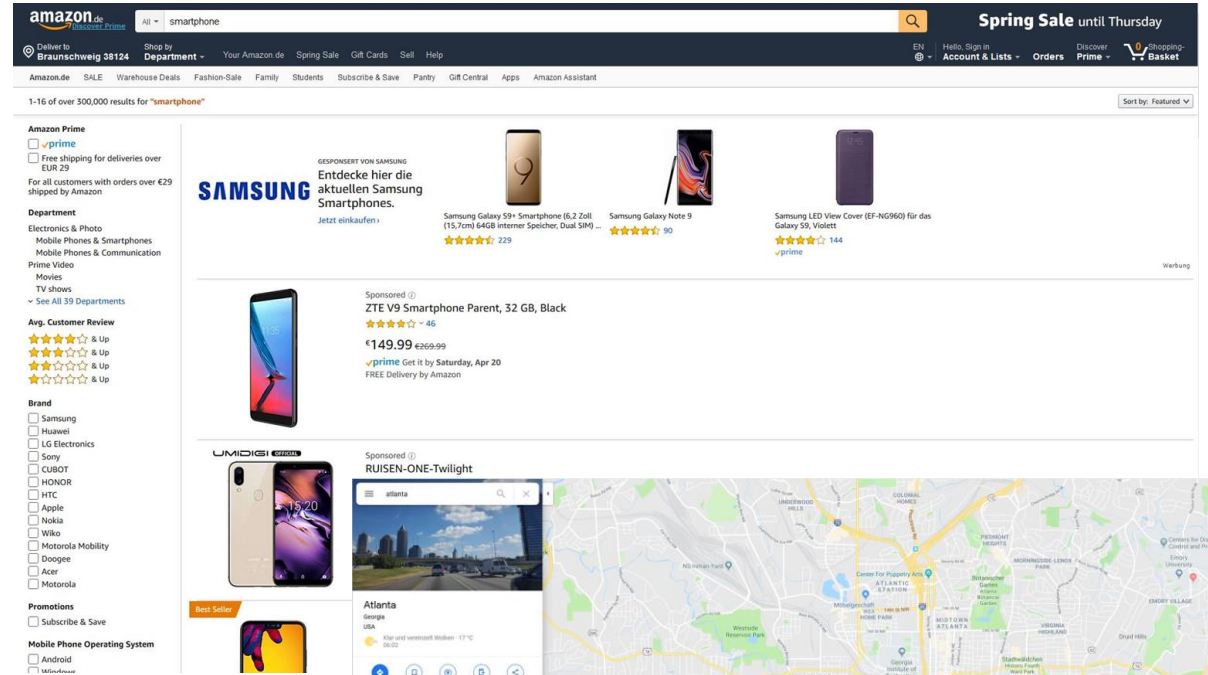


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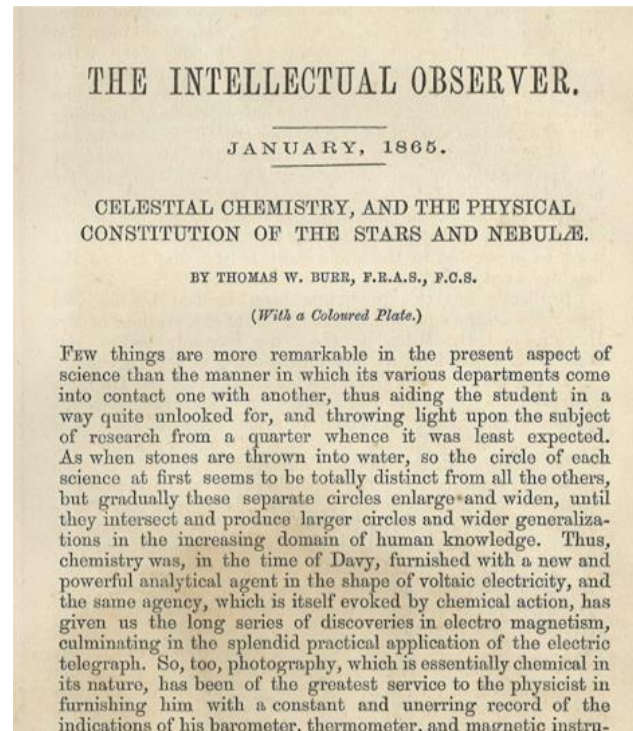
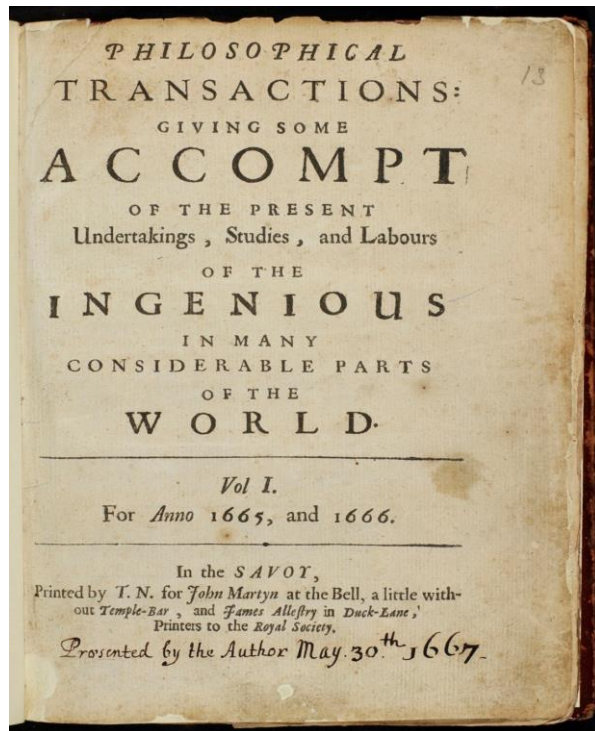


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Digitalization elsewhere



Digitization of scholarly communications



... almost four centuries

European Heart Journal (2017) 38, 362–372
doi:10.1093/eurheartj/ehw333

BASIC SCIENCE

Iron-regulatory proteins secure iron availability in cardiomyocytes to prevent heart failure

Saba Haddad^{1,2}, Yong Wang^{1,2}, Bruno Galy^{3,4}, Mortimer Korf-Klingebiel^{1,2}, Valentin Hirsch^{1,2}, Abdul M. Bawa^{1,2}, Fatemeh Rostami^{1,2}, Marc R. Reboll^{1,2}, Jörg Heineke², Ulrich Flügel⁵, Stephanie Groos⁶, André Renner⁷, Karl Toischer⁸, Fabian Zimmermann⁹, Stefan Engel¹⁰, Jens Jordan¹⁰, Johann Bauersachs², Matthias W. Hentze³, Kai C. Wollert^{1,2} and Tibor Kempf^{1,2*}

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Received 20 November 2015; revised 27 July 2016; accepted 27 July 2016; online ahead of print 21 August 2016

See page 373 for the editorial comment on this article (doi:10.1093/eurheartj/ehw333)

Aims Iron deficiency (ID) is associated with adverse outcomes in heart failure (HF) but the underlying mechanisms are incompletely understood. Intracellular iron availability is secured by two mRNA-binding iron-regulatory proteins (IRP), IRP1 and IRP2. We generated mice with a cardiomyocyte-targeted deletion of Irp1 and Irp2 to explore the functional implications of ID in the heart independent of systemic ID and anaemia.

Methods and results Iron content in cardiomyocytes was reduced in Irp-targeted mice. The animals were not anaemic and did not show a phenotype under baseline conditions. Irp-targeted mice, however, were unable to increase left ventricular (LV) systolic function in response to an acute dobutamine challenge. After myocardial infarction, Irp-targeted mice developed more severe LV dysfunction with increased HF mortality. Mechanistically, the activity of the iron-sulphur cluster-containing complex I of the mitochondrial electron transport chain was reduced in left ventricles from Irp-targeted mice. As demonstrated by extracellular flux analysis in vivo, mitochondrial respiration was preserved at baseline but failed to increase in response to dobutamine in Irp-targeted cardiomyocytes. As shown by ³¹P-magnetic resonance spectroscopy in vivo, LV phosphocreatine/ATP ratio declined during dobutamine stress in Irp-targeted mice but remained stable in control mice. Intravenous injection of ferric carboxymaltose replenished cardiac iron stores, restored mitochondrial respiratory capacity and isotropic reserve, and attenuated adverse remodelling after myocardial infarction in Irp-targeted mice but not in control mice. As shown by electrophoretic mobility shift assays, IRP activity was significantly reduced in LV tissue samples from patients with advanced HF and reduced LV tissue iron content.

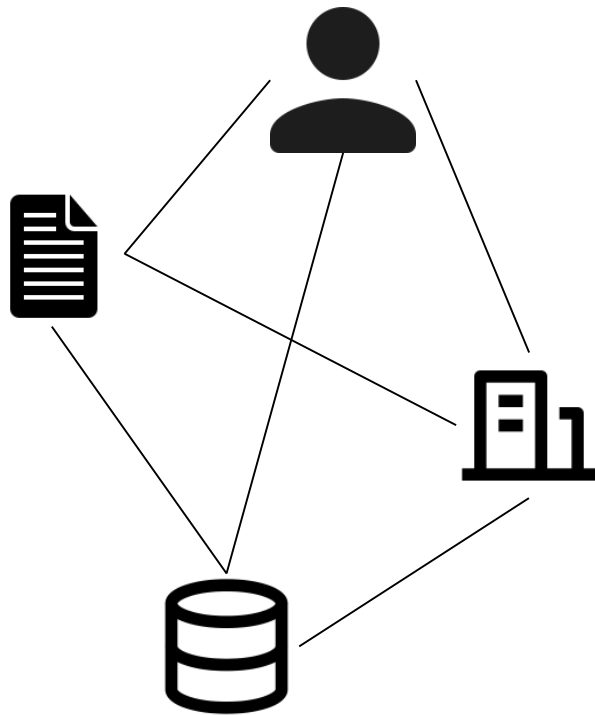
Conclusions ID in cardiomyocytes impairs mitochondrial respiration and adaptation to acute and chronic increases in workload. Iron supplementation restores cardiac energy reserve and function in iron-deficient hearts.

Keywords Iron deficiency • Heart failure • Energy metabolism • Extracellular flux analysis • ³¹P-Magnetic resonance spectroscopy

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<http://doi.org/10.1093/eurheartj/ehw333>

Not all that bad ...



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Scholarly Knowledge. Structured.



Situational Knowledge Representation for Traffic Observed by a Pavement Vibration Sensor Network

Markus Stocker, Mauno Rönkkö, and Mikko Kolehmainen

Abstract—Information systems that build on sensor networks often process data produced by measuring physical properties. These data can serve in the acquisition of knowledge for real-world situations that are of interest to information services and, ultimately, to people. Such systems face a common challenge, namely the considerable gap between the data produced by measurement and the abstract terminology used to describe real-world situations. We present and discuss the architecture of a software system that utilizes sensor data, digital signal processing, machine learning, and knowledge representation and reasoning to acquire, represent, and infer knowledge about real-world situations observable by a sensor network. We demonstrate the application of the system to vehicle detection and classification by measurement of road pavement vibration. Thus, real-world situations involve vehicles and information for their type, speed, and driving direction.

Index Terms—Knowledge acquisition, knowledge representation, machine learning, sensor data, sensor networks, traffic monitoring.

I. INTRODUCTION

WE propose a software system architecture and implementation for the continuous and automated representation of knowledge for real-world situations observable by a sensor network. In this paper, we demonstrate the application of the software system to intelligent transportation systems. Thus, real-world situations involve vehicles and information for their type, speed, and driving direction.

According to Finkelstein [1], “measurement is the process of empirical, objective, assignment of numbers to properties of objects or events of the real world in such a way as to describe them.” A sensor is a device that performs measurement, in that it transforms the signal of a physical property (e.g., heat) into numbers or, more generally, into data [2]. Sensor measurement is, hence, the process of recurrent application of such transformation for certain temporal and spatial locations. The result of sensor measurement is sensor data. Sensor data represent the change of the signal over time.

Despite recent advancements in sensor data management, processing, and query [2]–[4], as well as semantic description

of sensors and data [5]–[7], making sense of sensor data is an ongoing challenge [8]–[10] because of the difference in the degree to which sensor data represents information about a signal and information about, or related to, a physical property [11]. In other words, it is a challenge because of the considerable gap between data produced by measurement and abstract terminology [12] used by people to describe (the properties of) real-world objects or events.

We are interested in *situations* involving real-world objects that affect a physical property, for which a signal is measured by means of sensors. In this paper, vehicles are the real-world objects and road pavement vibration is the physical property. We present the architecture of a software system that utilizes digital signal processing, machine learning, and knowledge representation and reasoning to acquire, represent, and infer knowledge about real-world situations involving vehicles. The system aims at reducing the gap between road pavement vibration measurement data and abstract terminology used to describe real-world situations involving vehicles.

Digital signal processing techniques are iteratively applied to a sliding window over sensor data to enhance the vibration signal and to transform sensor data (time domain) into patterns (frequency domain). Machine learning is used to classify patterns. We employ multilayer perceptron (MLP) feedforward artificial neural networks [13]. Techniques in knowledge representation are utilized to formally represent domain concepts, instances, and relations. A concept of interest to our domain is the vibration sensor. The (installed) sensors are represented as instances of this concept. An instance may have a number of relations, e.g., to a spatial location. We represent sensors and observations using the Semantic Sensor Network Ontology (SSNO) [14].¹ SSNO is an “ontology for describing the capabilities of sensors, the act of sensing and the resulting observations” [15]. We employ the Situation Theory Ontology² (STO) [16] to represent knowledge about real-world situations, which are acquired from observations. The STO captures the key aspects of the situation theory developed by Barwise and Perry [17] and extended by Devlin [18]. The theory relates to the work on situation awareness by Endsley [19], [20] as it encompasses most of the concepts discussed in [16]. Both the SSNO and the STO serve as upper ontologies from which we extend to accommodate domain knowledge. The hybrid use of the SSNO and the STO allows for a multilevel abstraction of sensor measurement data and the use of appropriate terminology and formalization at each level.

Manuscript received April 12, 2013; revised August 16, 2013 and November 20, 2013; accepted December 22, 2013. Date of publication February 4, 2014; date of current version August 1, 2014. The infrastructure to access and collect vibration and camera data, as well as the data, are part of research funded by Tekes, the Finnish Funding Agency for Technology and Innovation (funding decision number 40075/09). The Associate Editor for this paper was P. Grosz.

The authors are with the Department of Environmental Science, University of Eastern Finland, 70211 Kuopio, Finland (e-mail: markus.stocker@uef.fi; mauno.ronkko@uef.fi; mikko.kolehmainen@uef.fi).

Digital Object Identifier 10.1109/TITS.2013.2296697

¹<http://port.oci.org/NET/SSNO>
²<http://vstology.com/ont/2008/STO/STO.owl>



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Situational Knowledge Representation for Traffic Observed by a Pavement Vibration Sensor Network

Information Science

Markus Stocker

Mauno Rönkkö

Mikko Kolehmainen

DOI: 10.1109/TITS.2013.2296697

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Contributions

Classification Detection Knowledge Representation Reasoning

Research problems

Road vehicle classification

Add to comparison

Contribution data

Employs

Machine Learning

Utilizes

A sensor network

Training Data

Waikato Environment for Knowledge Analysis

Yields

Classification performance for the three sensors (sd1, sd2, sd3)

Summary of precision and recall figures for the light and heavy classes of the vehicle classification task for the three sensors (sd1, sd2, sd3)

Summary of the confusion matrices for the vehicle classification task for the three sensors (sd1, sd2, sd3)

Methods

Materials

Results

II. MATERIALS AND METHODS

Here, we first present the materials used in this paper, namely the sensor network, the retrieved data, and software. We then detail the methods utilized to process sensor data, as well as to acquire, represent, and infer knowledge.

A. Materials

Road pavement vibration was measured using three CEF C3M01 accelerometer vibration sensors developed by Control Express Finland (CEF) Oy³ for condition monitoring and machinery maintenance. (CEF C3M01 sensors are currently manufactured by Webrosensor Oy⁴ as WBS CM301.) The sensor network was installed at the training site of the Finnish Emergency Services College, Kuopio, Finland. The site is used for emergency response training in simulated situations involving, for instance, vehicles or buildings that are on fire. The area can be accessed by vehicle, and its paved light traveled roads are for different types of vehicles, such as ambulances and fire trucks. The three accelerometer vibration sensors were part of a wider sensor network that consisted of chemical sensors, weather stations, acoustic sensors, and surveillance cameras. The sensor network was installed and maintained for a Finnish research project that aimed at the development of systems for the monitoring of an operational environment.

The accelerometer vibration sensors—hereafter referred to as sensing devices sd_1 , sd_2 , and sd_3 —were installed with a relative distance of approximately 45 m at the right side (with respect to the surveillance camera, described later) along one of the roads at the training site. Each sensor was mounted on a metal bar that penetrated approximately 1 m into the ground, roughly 0.5 m below the paved road surface. The sensors measured ground vibration, including vibration induced by vehicles. We visually monitored the road using an AXIS 211W Wireless Network Camera with an Outdoor Antenna Kit AXIS 211W [21]. The camera was positioned on top of a viewpoint tower located nearby the road and directed toward the monitored road section.

Research problems

 Add to comparison

Road vehicle classification

Contribution data

[← Back](#)
[Mair](#) [A sensor network](#) [↻](#)

Location	Emergency Services Academy Finland Training Ground
Sub system	Accelerometer vibration sensor (sd1)
	Accelerometer vibration sensor (sd2)
	Accelerometer vibration sensor (sd3)
	AXIS 211W Wireless Network Camera

II. MATERIALS AND METHODS

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Research problems Add to comparison

Road vehicle classification

← Back Main A set Accelerometer vibration sensor (sd1) [↗](#)

Datasheet	WBS CM301 Datasheet
Manufacturer	Webrosensor Oy
Observes	vibration

Accelerometer vibration sensor (sd3)

AXIS 211W Wireless Network Camera

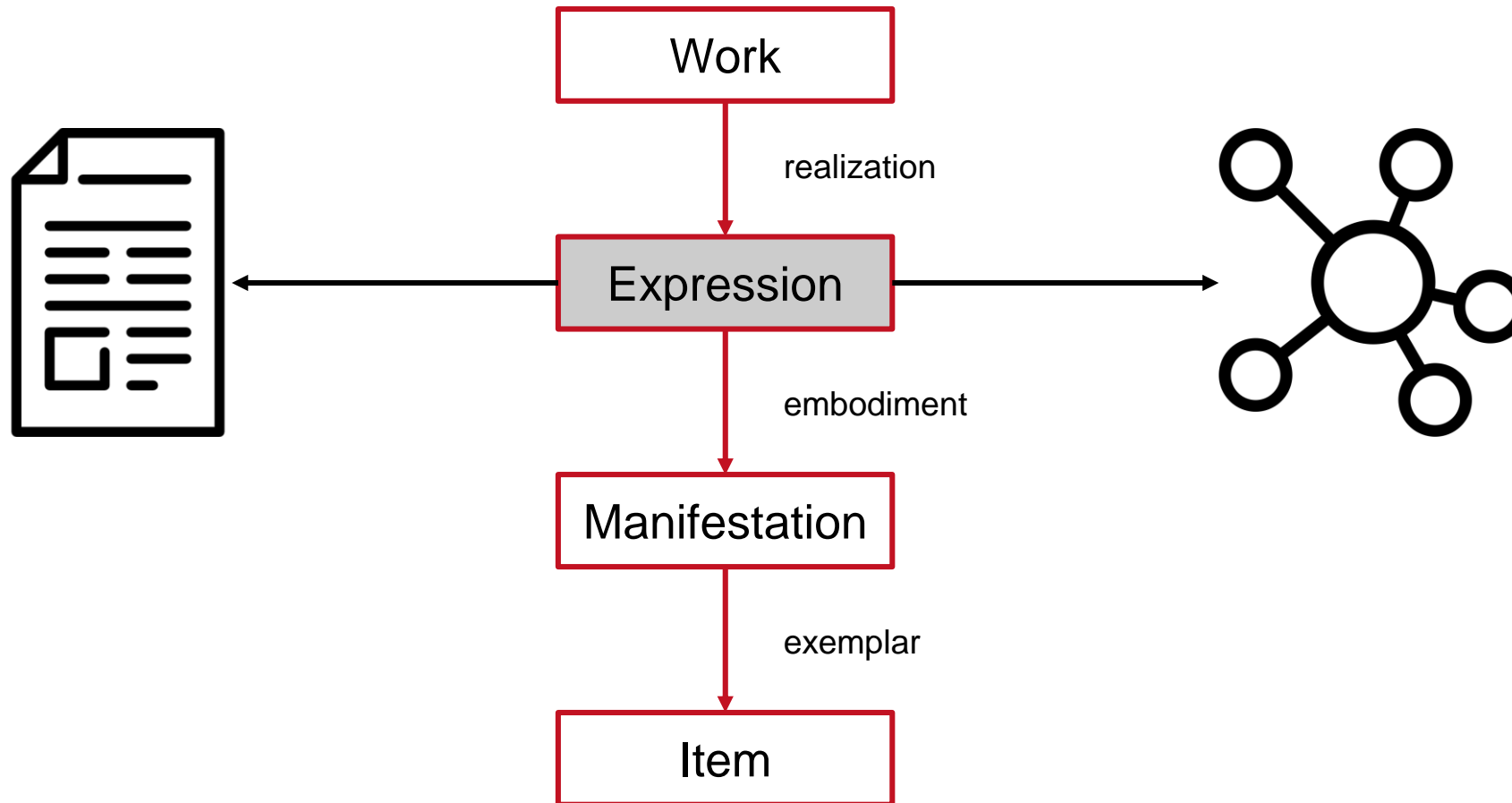
TABLE III
 SUMMARY OF PRECISION (P) AND RECALL (R) FIGURES FOR THE
 CLASSES (C) *no-vehicle* (NV) AND *vehicle* (V) OF THE VEHICLE
 DETECTION (VD) TASK AND THE CLASSES *light* (L) AND *heavy* (H)
 OF THE VEHICLE CLASSIFICATION (VC) TASK FOR THE
 THREE SENSING DEVICES (SD)

	C	SD	P	R
VD	NV	<i>sd</i> ₁	0.967	0.933
		<i>sd</i> ₂	0.971	0.943
		<i>sd</i> ₃	0.953	0.97
	V	<i>sd</i> ₁	0.768	0.874
		<i>sd</i> ₂	0.928	0.963
		<i>sd</i> ₃	0.962	0.94
VC	H	<i>sd</i> ₁	0.83	0.83
		<i>sd</i> ₂	0.721	0.778
		<i>sd</i> ₃	0.842	0.774
	L	<i>sd</i> ₁	0.8	0.8
		<i>sd</i> ₂	0.788	0.732
		<i>sd</i> ₃	0.816	0.873

← Back Main Sum Class: heavy; Sensor: sd3 [↻](#)

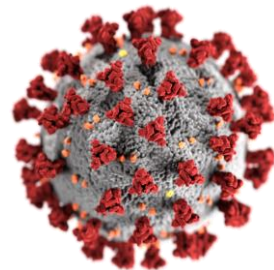
Class	heavy
Precision	0.842
Recall	0.774
Sensor	sd3

Functional Requirements for Bibliographic Records



Example

COVID-19 basic reproduction number



COVID-19 e-print

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[Submitted on 20 Mar 2020]

The early phase of the COVID-19 outbreak in Lombardy, Italy

Cereda D, Tirani M, Rovida F, Demicheli V, Ajelli M, Poletti P, Trentini F, Guzzetta G, Marziano V, Barone A, Magoni M, Deandrea S, Diurno G, Lombardo M, Faccini M, Pan A, Bruno R, Pariani E, Grasselli G, Piatti A, Gramegna M, Baldanti F, Melegaro A, Merler S

In the night of February 20, 2020, the first case of novel coronavirus disease (COVID-19) was confirmed in the Lombardy Region, Italy. In the week that followed, Lombardy experienced a very rapid increase in the number of cases. We analyzed the first 5,830 laboratory-confirmed cases to provide the first epidemiological characterization of a COVID-19 outbreak in a Western Country. Epidemiological data were collected through standardized interviews of confirmed cases and their close contacts. We collected demographic backgrounds, dates of symptom onset, clinical features, respiratory tract specimen results, hospitalization, contact tracing. We provide estimates of the reproduction number and serial interval. The epidemic in Italy started much earlier than February 20, 2020. At the time of detection of the first COVID-19 case, the epidemic had already spread in most municipalities of Southern-Lombardy. The median age for of cases is 69 years (range, 1 month to 101 years). 47% of positive subjects were hospitalized. Among these, 18% required intensive care. The mean serial interval is estimated to be 6.6 days (95% CI, 0.7 to 19). We estimate the basic reproduction number at 3.1 (95% CI, 2.9 to 3.2). We estimated a decreasing trend in the net reproduction number starting around February 20, 2020. We did not observe significantly different viral loads in nasal swabs between symptomatic and asymptomatic. The transmission potential of COVID-19 is very high and the number of critical cases may become largely unsustainable for the healthcare system in a very short-time horizon. We observed a slight decrease of the reproduction number, possibly connected with an increased population awareness and early effect of interventions. Aggressive containment strategies are required to control COVID-19 spread and catastrophic outcomes for the healthcare system.

Subjects: [Populations and Evolution \(q-bio.PE\)](#)

Cite as: [arXiv:2003.09320 \[q-bio.PE\]](#)

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Results

The epidemic in Italy started much earlier than February 20, 2020. At the time of detection of the first COVID-19 case, the epidemic had already spread in most municipalities of Southern-Lombardy. The median age for of cases is 69 years (range, 1 month to 101 years). 47% of positive subjects were hospitalized. Among these, 18% required intensive care. The mean serial interval is estimated to be 6.6 days (95% CI, 0.7 to 19). We estimate the basic reproduction number at 3.1 (95% CI, 2.9 to 3.2). We estimated a decreasing trend in the net reproduction number starting around February 20, 2020. We did not observe significantly different viral loads in nasal swabs between symptomatic and asymptomatic.

Here we provide an analysis of the first 5,830 laboratory-confirmed cases reported in Lombardy, with date of symptoms onset over the period from January 14 to March 8, 2020. Epidemiological analyses of the confirmed cases and their background demographic and exposure characteristics are presented here as well as the transmission dynamics of the infection within the Region. Also, the virological analysis on a subsample of the reported cases is included to provide preliminary assessment of the level of the viral load among symptomatic and asymptomatic cases.



View paper

Graph view Edit

The early phase of the COVID-19 outbreak in Lombardy, Italy

- 2020 Virology Cereda D Tirani M Rovida F Demicheli Ajelli M Poletti P Trentini F Guzzetta G Marziano Barone A Magoni M Deandrea S Diurno G Lombardo M Faccini M Pan A Bruno R Pariani E Grasselli G Piatti A Gramegna M Baldanti F Melegaro A Merler S

Published in: arXiv.org

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Contribution 1

Research problems Add to comparison

COVID-19 reproductive number

Contribution data

Table with 2 columns: Metric and Value. Rows include 95% Confidence interval (2.9-3.2), Location (Lombardy, Italy), R0 estimates (average) (3.1), and Study date (2020-01-14/2020-03-08).

What does ORKG enable?

Contribution comparison 31

View

+ Add contribution

More ▾

COVID-19 Reproductive Number Estimates

Method: Intelligent merge

Comparison of published reproductive number estimates for the COVID-19 infectious disease

 June 2020 Allard Oelen Jennifer D'Souza Markus Stocker Lars Vogt Kheir Eddine Farfar Muhammad Haris
 Kamel Fadel Mohamad Yaser Jaradeh Vitalis Wiens

 DOI: [10.48366/r44930](https://doi.org/10.48366/r44930)

Properties	The early phase of the COVID-19 outbreak in Lombardy, Italy Contribution 1 - 2020	Transmission potential of COVID-19 in Iran Contribution 1 - 2020	Transmission potential of COVID-19 in Iran Contribution 2 - 2020	Esti on s Con
Location	Lombardy, Italy	Iran	Iran	
Time period	Time interval	Time interval	Time interval	
Has beginning	2020-01-14	2020-02-19	2020-02-19	
Has end	2020-03-08	2020-02-29	2020-02-29	
Basic reproduction number	Basic reproduction number estimate value specification	Basic reproduction number estimate value specification	Basic reproduction number estimate value specification	Basic reproduction number estimate value specification
Has value	3.1	3.6	3.58	
Confidence interval (95%)	Confidence interval (95%)	Confidence interval (95%)	Confidence interval (95%)	
Lower confidence limit	2.9	3.4	1.29	
Upper confidence limit	3.2	4.2	8.46	

Name	Last Modified
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R0-estimates-se...	9 minutes ago

```
[ ]: import requests
import datetime
import pandas as pd
import numpy as np
from orkg import ORKG
from bokeh.io import export_png
from bokeh.models import ColumnDataSource, HoverTool, WheelZoomTool, ResetTool, SaveTool, PanTool, DatetimeTickFormatter, Whisker
from bokeh.plotting import figure, show, output_notebook

output_notebook()

[ ]: orkg = ORKG(host='https://orkg.org/orkg', simcomp_host='https://orkg.org/orkg/simcomp')

df = orkg.contributions.compare_dataframe(comparison_id='R44930')

[ ]: dates = np.array([datetime.date.fromisoformat(x) for x in df.loc['has end', :]])
values = np.float32(df.loc['Has value', :])
lower = np.array([np.float32(x) if x else np.nan for x in df.loc['Lower confidence limit', :]])
upper = np.array([np.float32(x) if x else np.nan for x in df.loc['Upper confidence limit', :]])

[ ]: hover1 = HoverTool(
    tooltips=[
        ('Date', '@date{%F}'),
        ('R0', '@value{0.2f}'),
        ('95% CI', '@lower{0.2f}-@upper{0.2f}')
    ],
    formatters={
        '@date': 'datetime',
        '@{value}': 'printf',
        '@{lower}': 'printf',
        '@{upper}': 'printf'
    }
)

df = pd.DataFrame(data=dict(date=dates, value=values, lower=lower, upper=upper))
source = ColumnDataSource(df)
p = figure(x_axis_type="datetime", y_range=(0, 9), plot_width=800, plot_height=350, tools=[hover1, WheelZoomTool(), PanTool(), ResetTool(), SaveTool()])
p.xaxis.formatter=DatetimeTickFormatter(days=['%d %b'])
p.yaxis.axis_label = 'basic reproduction number'
p.circle('date', 'value', source=source, size=7, color='purple')
p.add_layout(
    Whisker(source=source, base='date', upper='upper', lower='lower', level='overlay')
)
show(p)

[ ]: export_png(p, filename='img/R0-estimates-plot.png')
```


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R0-estimates-pl...	4 minutes ago
R0-estimates-se...	9 minutes ago

Launcher R0-estimates-plot.ipynb

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[ ]: import requests
import datetime
import pandas as pd
import numpy as np
from orkg import ORKG
from bokeh.io import export_png
from bokeh.models import ColumnDataSource, HoverTool, WheelZoomTool, ResetTool, SaveTool, PanTool, DatetimeTickFormatter, Whisker
from boki
```

```
output_n
```

```
[ ]: orkg = ORKG
```

```
df = orkg
```

```
[ ]: dates =
```

```
values =
```

```
lower =
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upper =
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[ ]: hover1 =
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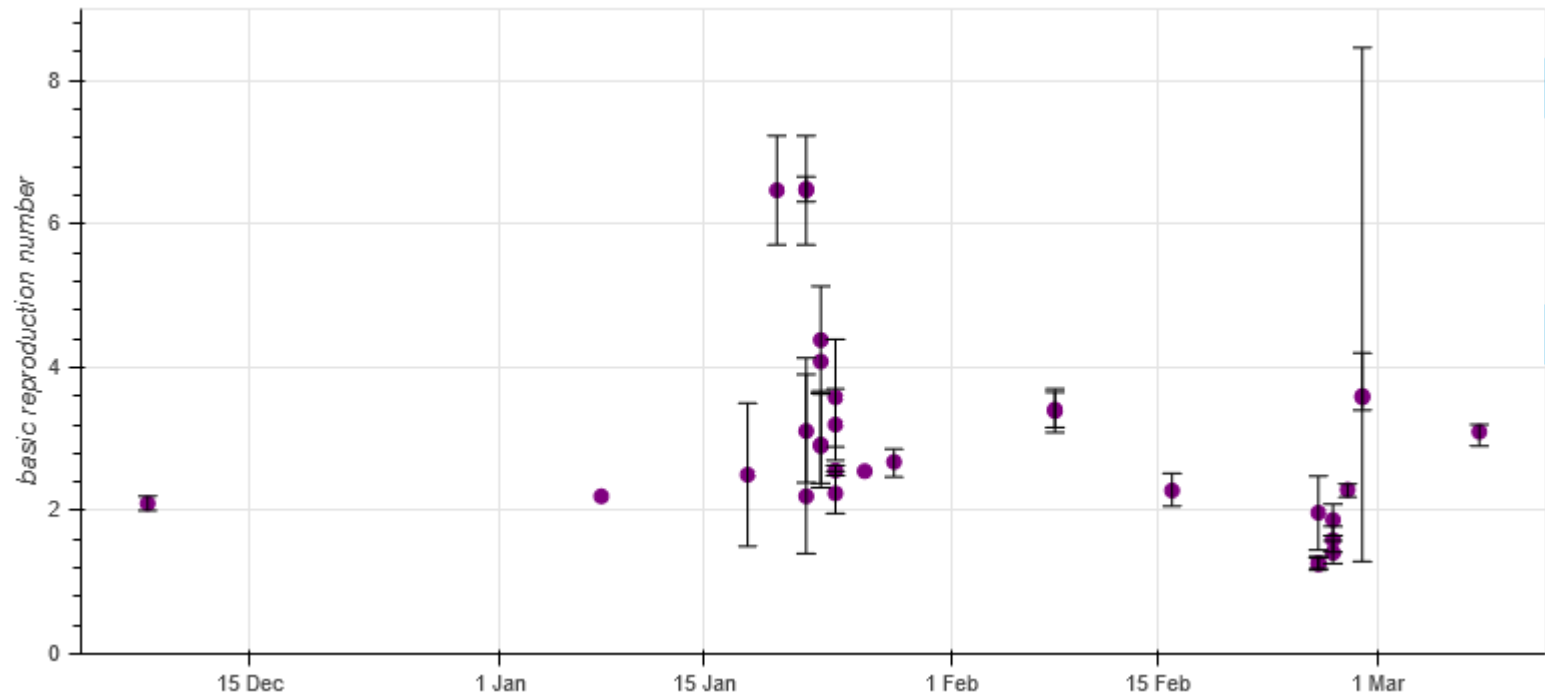
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```
df = pd.
```

```
source = ColumnDataSource(df)
```

```
p = figure(x_axis_type="datetime", y_range=(0, 9), plot_width=800, plot_height=350, tools=[hover1, WheelZoomTool(), PanTool(), ResetTool(), SaveTool()])
```

```
p.xaxis.formatter=DatetimeTickFormatter(days=['%d %b'])
```

```
p.yaxis.axis_label = 'basic reproduction number'
```

```
p.circle('date', 'value', source=source, size=7, color='purple')
```

```
p.add_layout(
```

```
    whisker(source=source, base='date', upper='upper', lower='lower', level='overlay')
```

```
)
```

```
show(p)
```

```
[ ]: export_png(p, filename='img/R0-estimates-plot.png')
```

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Launcher R0-estimates-plot.ipynb

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Name	Last Modified
img	9 minutes ago
R0-estimates-pl...	4 minutes ago
R0-estimates-se...	9 minutes ago

```
[ ]: import requests
import datetime
import pandas as pd
import numpy as np
from orkg import ORKG
from bokeh.io import export_png
from bokeh.models import ColumnDataSource, HoverTool, WheelZoomTool, ResetTool, SaveTool, PanTool, DatetimeTickFormatter, Whisker
```

```
orkg = ORKG(host='https://orkg.org/orkg', simcomp_host='https://orkg.org/orkg/simcomp')
```

```
df = orkg.contributions.compare_dataframe(comparison_id='R44930')
```

```
dates = np.array([datetime.date.fromisoformat(x) for x in df.loc['has end', :]])
```

```
values = np.float32(df.loc['Has value', :])
```

```
lower = np.array([np.float32(x) if x else np.nan for x in df.loc['Lower confidence limit', :]])
```

```
upper = np.array([np.float32(x) if x else np.nan for x in df.loc['Upper confidence limit', :]])
```











```
    ('95% CI', '@lower{0.fff}-@upper{0.fff}')
],
formatters={
    '@date': 'datetime',
    '@{value}': 'printf',
    '@{lower}': 'printf',
    '@{upper}': 'printf'
}
)

df = pd.DataFrame(data=dict(date=dates, value=values, lower=lower, upper=upper))
source = ColumnDataSource(df)
p = figure(x_axis_type="datetime", y_range=(0, 9), plot_width=800, plot_height=350, tools=[hover1, WheelZoomTool(), PanTool(), ResetTool(), SaveTool()])
p.xaxis.formatter=DatetimeTickFormatter(days=['%d %b'])
p.yaxis.axis_label = 'basic reproduction number'
p.circle('date', 'value', source=source, size=7, color='purple')
p.add_layout(
    Whisker(source=source, base='date', upper='upper', lower='lower', level='overlay')
)
show(p)
```

```
[ ]: export_png(p, filename='img/R0-estimates-plot.png')
```

COVID-19 Reproductive Number Estimates



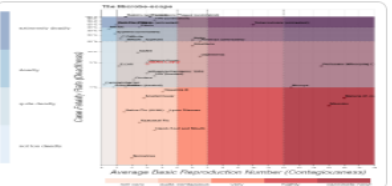
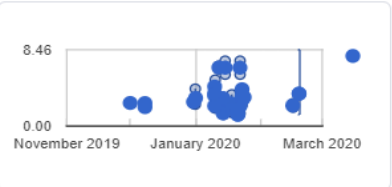
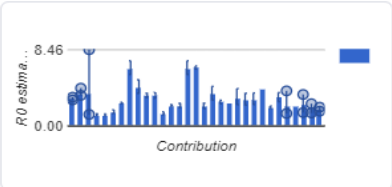
 June 2020  Allard Oelen  Jennifer D'Souza  Markus Stocker  Lars Vogt  Kheir Eddine Farfar  Muhammad Haris  Kamel Fadel
 Mohamad Yaser Jaradeh  Vitalis Wiens

Comparison of published reproductive number estimates for the COVID-19 infectious disease

DOI: <https://doi.org/10.48366/r44930>

Visualizations with Jupyter

Visualizations for reproduction number



Transmission potential of COVID-19 in Iran <https://doi.org/10.1101/2020.03.08.20030643>

 2 Citations

Description Other Identifiers Creators Registration

We computed reproduction number of COVID-19 epidemic in Iran using two different methods. We estimated R_0 at 3.6 (95% CI, 3.2, 4.2) (generalized growth model) and at 3.58 (95% CI, 1.29, 8.46) (estimated epidemic doubling time of 1.20 (95% CI, 1.05, 1.44) days) respectively. Immediate social distancing measures are recommended.

2 Citations

COVID-19 Reproductive Number Estimates

Allard Oelen, Jennifer D'Souza, Markus Stocker, Lars Vogt, Kheir Eddine Farfar, Muhammad Haris, Kamel Fadel, Mohamad Yaser Jaradeh & Vitalis Wiens

Comparison published 2020 in [Open Research Knowledge Graph \(ORKG\)](#)

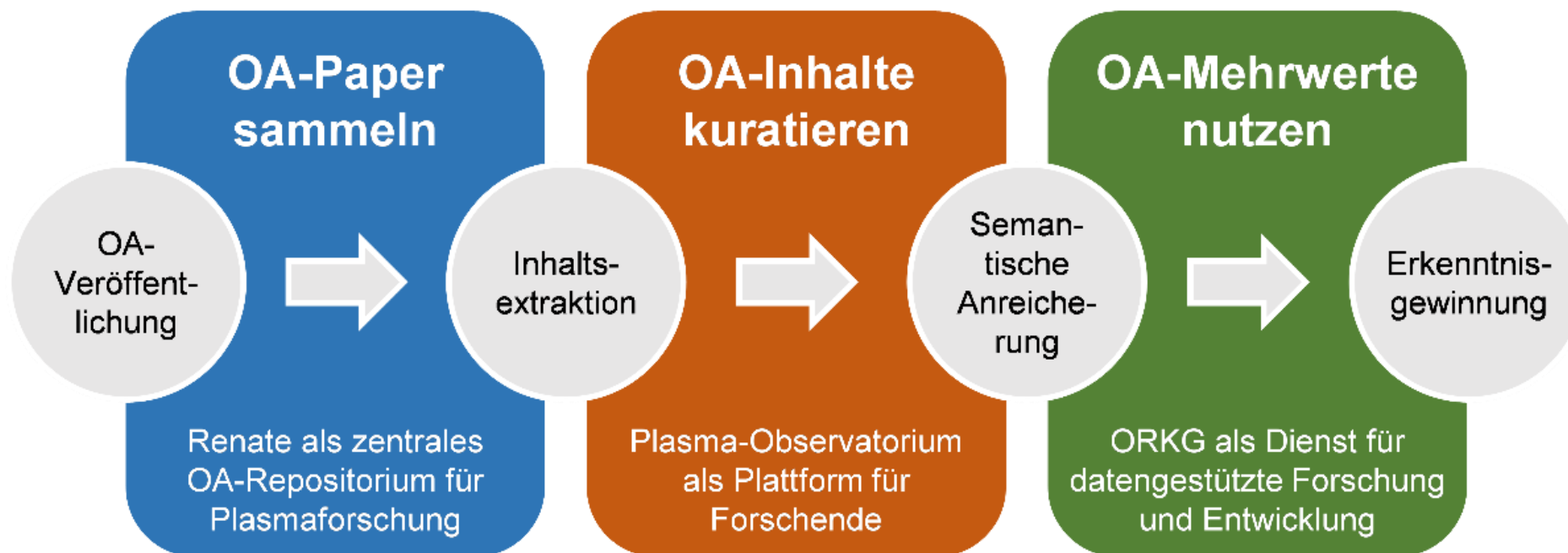
Comparison of published reproductive number estimates for the COVID-19 infectious disease

DOI registered October 16, 2020 via DataCite.

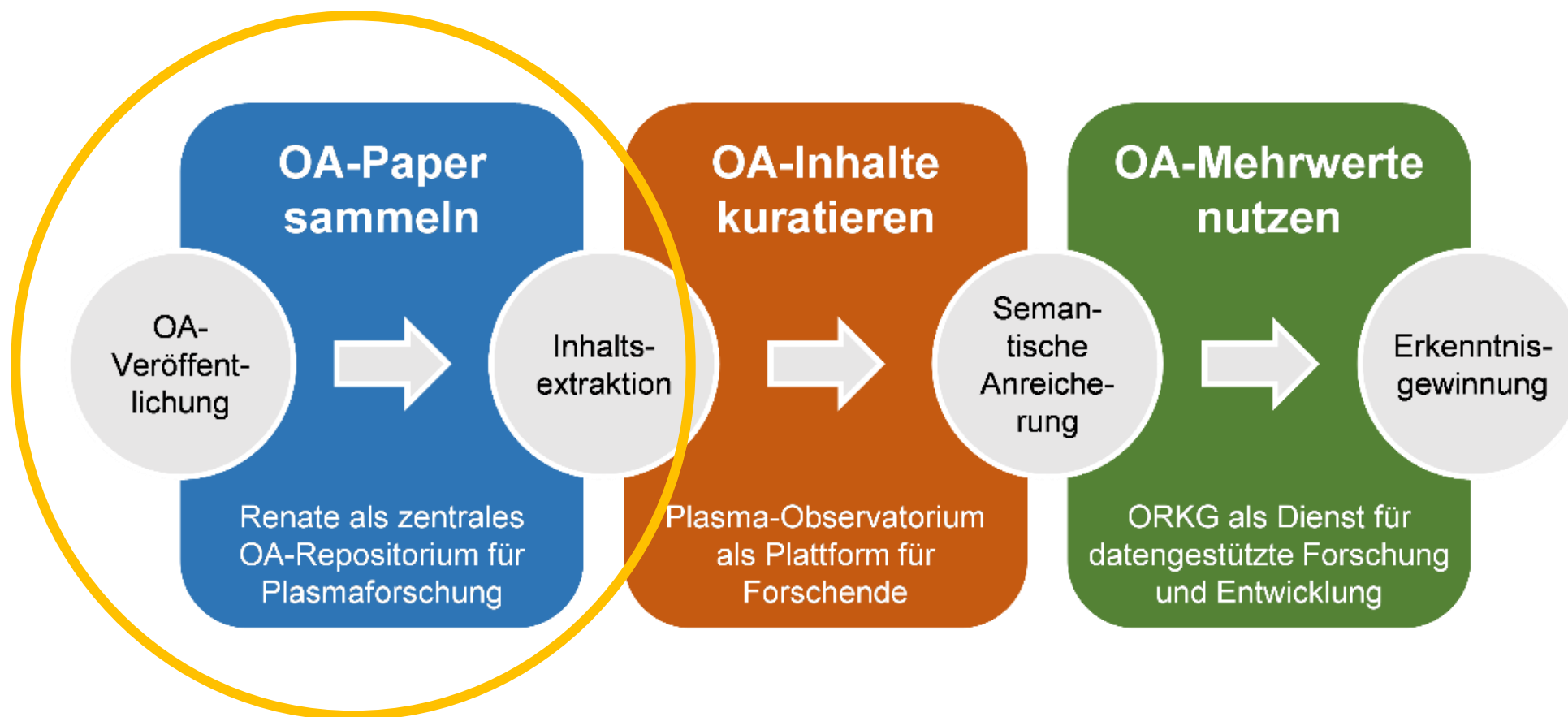
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The Process in “Mehr-OA”

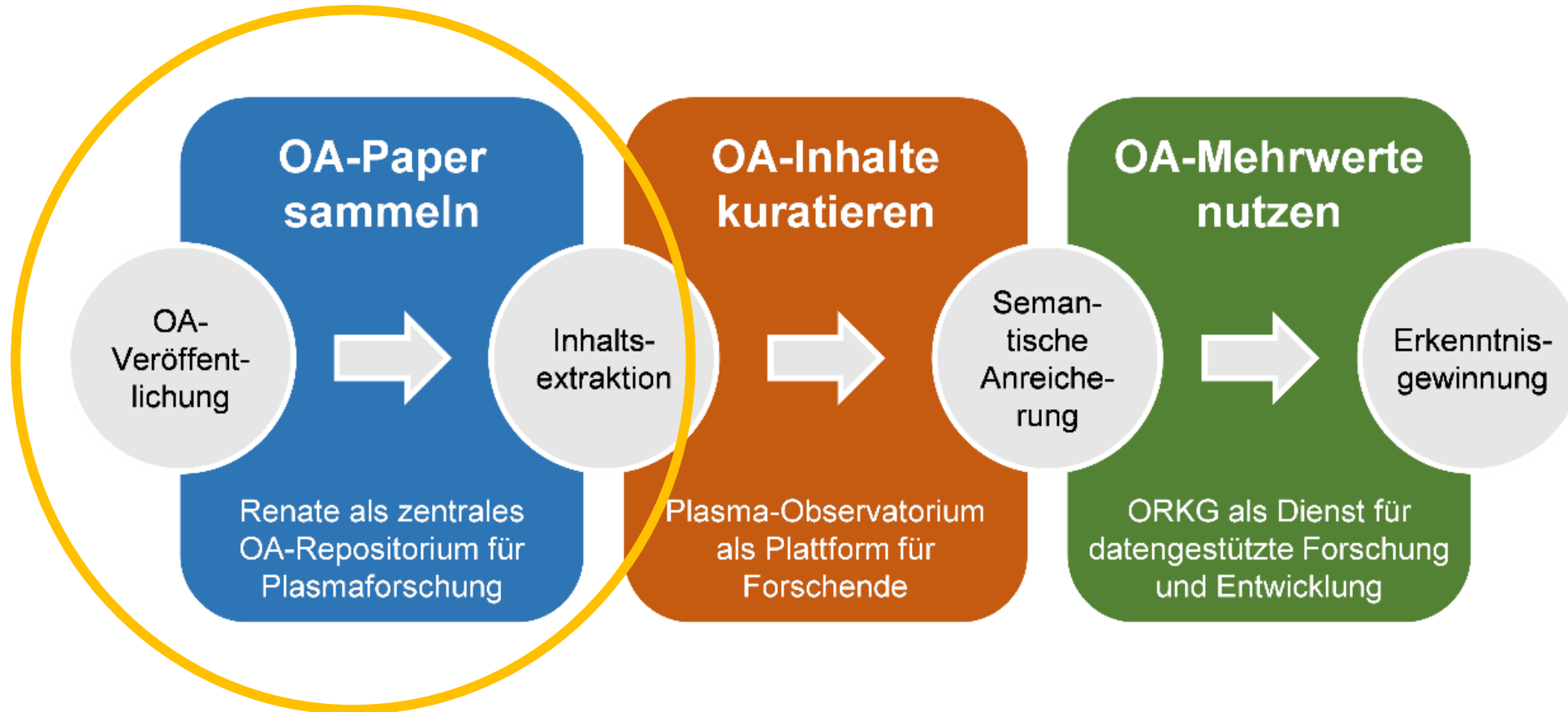


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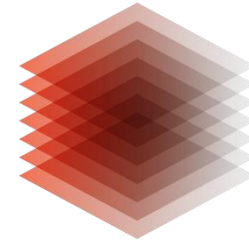
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Take aways

- Scholarly work can be realized as expressions other than an article
- Content can also be realized so that it is more machine readable
- Thus easier to reuse, for machines and people
- Turning the vision and prototypes into reality is very challenging
- Requires a significant rethinking and rewiring of the current approaches and infrastructure

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Questions

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