

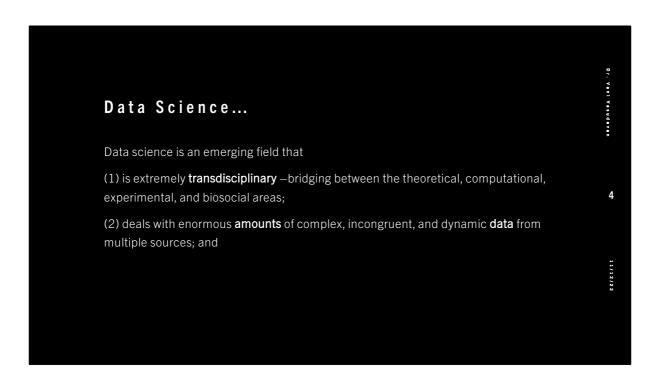
- The purpose of computing is **insight**, not numbers.— Richard W. Hamming (**Data Science**)
- A data scientist is someone who knows more **statistics** than a computer scientist and more **computer** science than a statistician.— Josh Blumenstock (Mathematics)
- On two occasions I have been asked, "Pray, Mr. Babbage, if you put into the machine wrong figures, will the right answers come out?" . . . I am not able to rightly apprehend the kind of confusion of ideas that could provoke such a question. – Charles Babbage (Data Wrangling)

- Money is a **scoreboard** where you can rank how you're doing against other people.— Mark Cuban (Measures)
- It is easy to lie with statistics, but easier to lie without them. (Statistical Analysis)
- At their best, **graphics** are instruments for reasoning.— Edward Tufte (**Data Visualization**)

## Some More Quotes!!!

- All models are wrong, but some models are useful. George Box (Mathematical Models)
- Any sufficiently advanced form of cheating is indistinguishable from **learning**.— Jan Schaumann (**Machine Learning**)
- A change in quantity also entails a change in quality.— Friedrich Engel (Big Data) https://www.internetlivestats.com/

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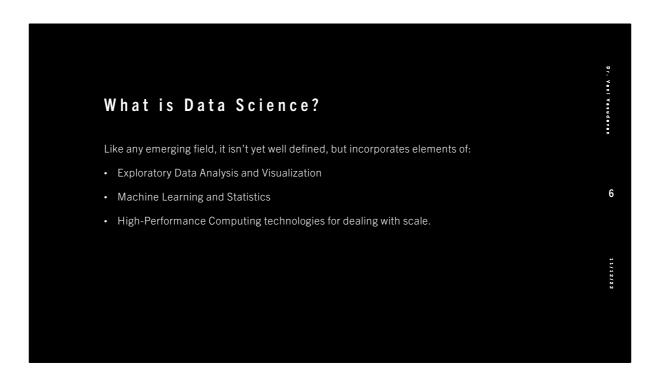


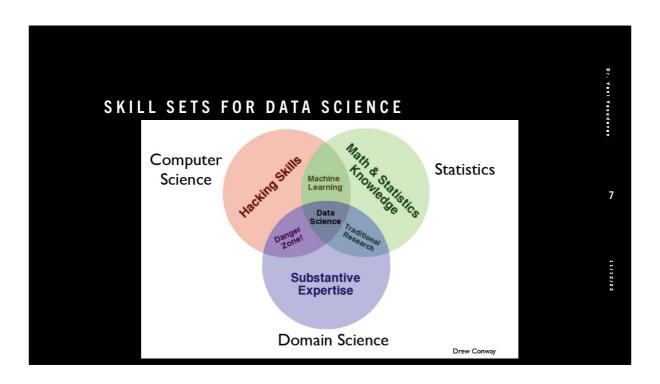
Source: Data Science and Predictive Analytics Ivo D. Dinov, "Biomedical and Health Applications using R", Springer 2018 (3) aims to develop algorithms, methods, tools, and services capable of ingesting such datasets and generating semiautomated decision support systems.

The latter can mine the data for patterns or motifs, predict expected outcomes, suggest clustering or labeling of retrospective or prospective observations, compute data signatures or fingerprints, extract valuable information, and offer evidence-based actionable knowledge.

Data science techniques often involve data manipulation (wrangling), data harmonization and aggregation, exploratory or confirmatory data analyses, predictive analytics, validation, and fine-tuning.

Source : Data Science and Predictive Analytics Ivo D. Dinov, "Biomedical and Health Applications using R", Springer 2018



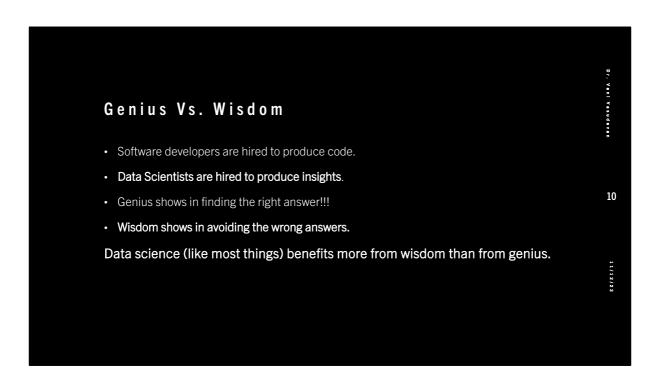


source: Steven S. Skiena, "The Data Science Design Manual", Springer 2017. Some more resources:

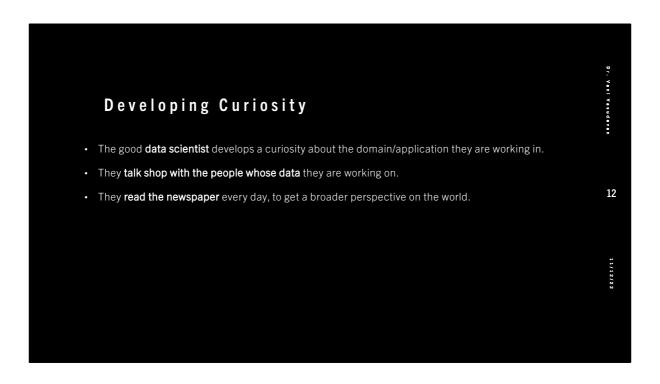
https://towardsdatascience.com/introduction-to-statistics-e9d72d818745 https://deepai.org/machine-learning-glossary-and-terms/data-science https://www.devopsschool.com/blog/what-is-data-science-advantages-and-disadvantages-of-data-science/

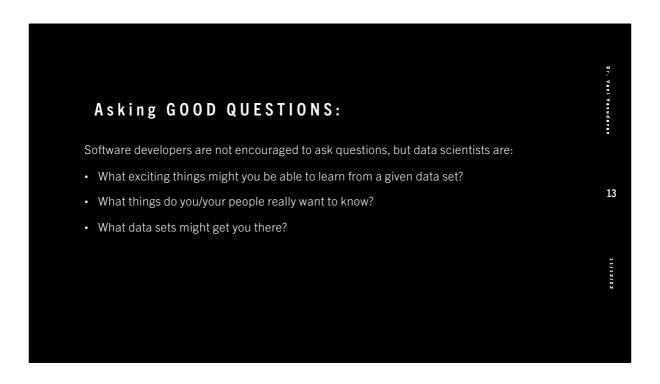
# Appreciating Data Computer Scientists do not naturally appreciate data: it's just stuff to run through a program. The usual way to test algorithm performance is to run the implementation on "random data". But, interesting data sets are a scarce resource, which requires hard work and imagination to obtain.

# Computer Vs. Real Scientists Scientists strive to understand the complicated and messy natural world, while computer scientists build their own clean and organized virtual worlds. Thus: Nothing is ever completely true or false in science, while everything is either true or false in Computer Science / Mathematics. Scientists are data-driven, while computer scientists are algorithm-driven. Scientists obsess about discovering things, which computer scientists invent rather than discover. Scientists are comfortable with the idea that data has errors; computer scientists are not.

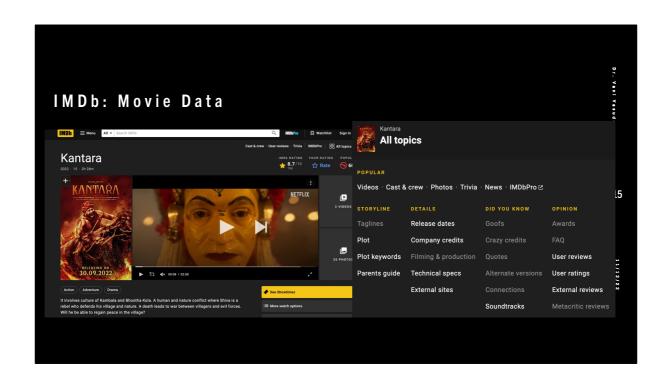


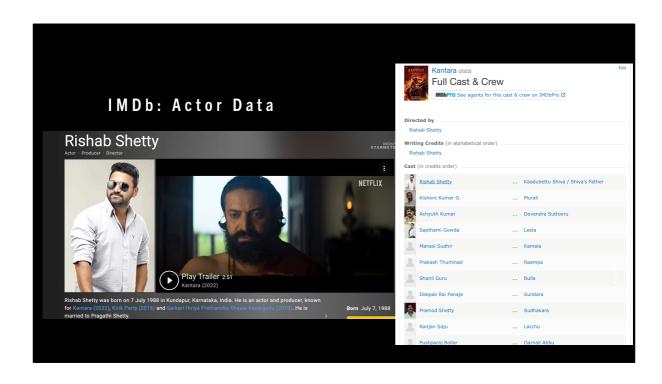


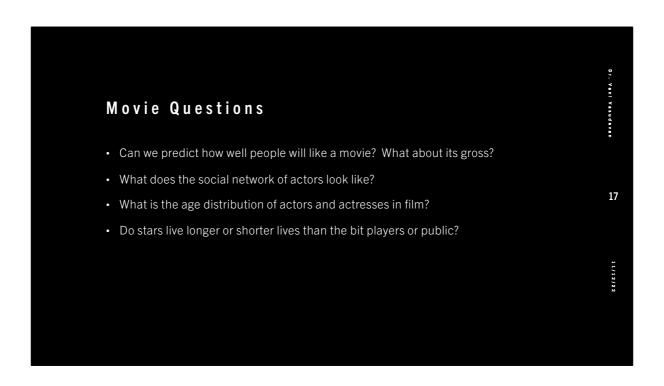


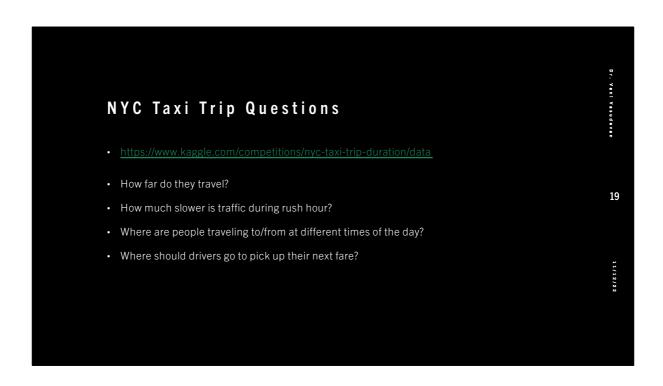


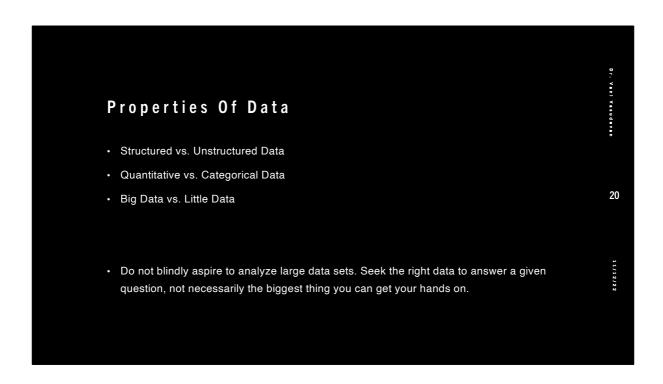
# LET'S PRACTICE ASKING QUESTIONS! • Who, What, Where, When, and Why on the following datasets: 1. International Movie Database (IMDB) 2. New York City Taxi Trip Duration









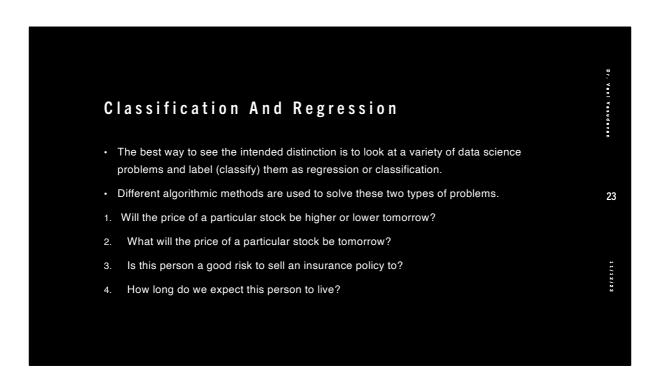


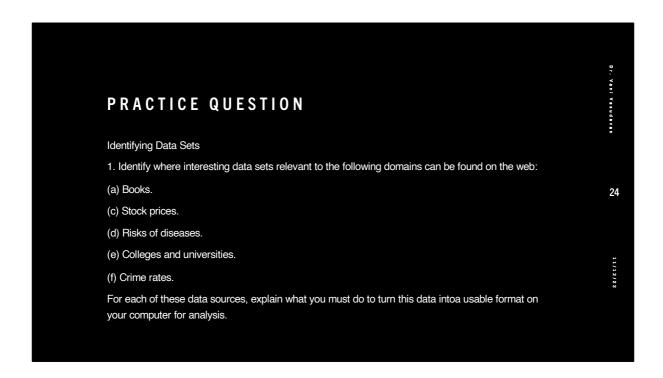
• Two types of problems arise repeatedly in **traditional data science and pattern recognition applications**, the challenges of classification and regression.

Classification: Often, we seek to assign a label to an item from a discrete set of possibilities. Such problems as predicting the winner of a particular sporting contest (team A or team B?) or deciding the genre of a given movie (comedy, drama, or animation?) are classification problems, since each entail selecting a label from the possible choices.

21

11/12





# The Data Science Pipeline 1. Get or collect data 2. Manipulate and process data 3. Modeling and analysis 25 4. Visualize, evaluate, present, and communicate

## Some Useful Web Resources to Kick Start Your Learning And Research!

- https://cognitiveclass.ai/ Data Science and Cognitive Computing Courses
- <a href="https://www.kdnuggets.com/">https://www.kdnuggets.com/</a> Site on Al, Analytics, Big Data, Data Mining, Data Science, and ML <a href="https://www.kdnuggets.com/">https://www.kdnuggets.com/</a> ML & DS community
- <a href="https://data.gov/">https://data.gov/</a> US government data
- http://archive.ics.uci.edu/ml/index.php ML Repository
- https://homepages.ecs.vuw.ac.nz/~marslast/MLbook.html Stephen Marsland homepage
- https://www.cs.waikato.ac.nz/ml/weka/courses.html Waikato University Weka MOOC
- https://nptel.ac.in/courses/106/106/106106202/- NPTEL Machine Learning
- Rohit singh, tommi jaakkola, and ali mohammad. 6.867 Machine learning. Fall 2006. Massachusetts institute of technology: MIT opencourseware, <a href="https://ocw.mit.edu">https://ocw.mit.edu</a>.
- Leslie kaelbling, tomás lozano-pérez, isaac chuang, and duane boning. 6.036 introduction to machine learning. Fall 2020. Massachusetts institute of technology: MIT opencourseware, <a href="https://ocw.mit.edu.">https://ocw.mit.edu.</a>
- $\qquad \underline{ \text{https://ocw.mit.edu/courses/hst-953-collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science for healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-fall-2020/collaborative-data-science-for-healthcare-fall-2020/collaborative-data-science-fall-2020/collaborative-fall-2020/collaborative-fall-2020/collaborative-fall-2020/collaborative-fall-2020/collaborative-fall-2020/collaborative-fall-$
- https://ocw.mit.edu/courses/15-062-data-mining-spring-2003/

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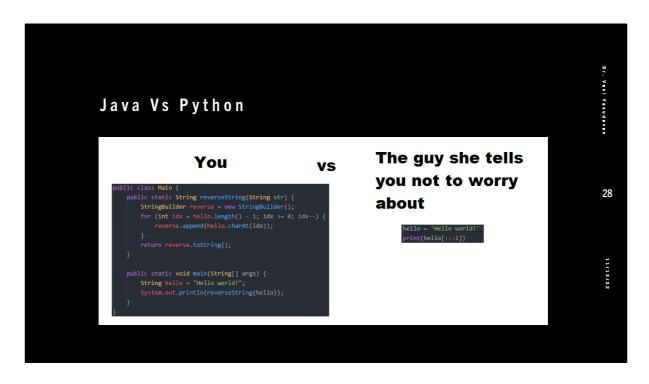
### Data Science Tools

- 1. Python(Most known)
- Python is one of the most dominant languages in the field of data science today because of
  its flexibility, ease of use in terms of syntax, open-source nature, and ability to handle,
  clean, manipulate, visualize, and analyze data.

27

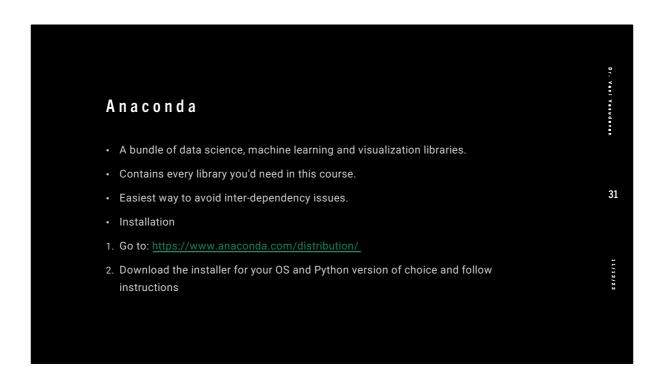
 Python was essentially developed as a programming language. However, it offers a wide range of libraries, such as TensorFlow, Keras, PyTorch, Seaborn, etc., that are attractive for both programmers and data scientists alike. Moreover, there are various other tools connected to and built with the help of Python, such as Dask, SciPy, Cython, Matplotlib, and High-Performance Analytics Toolkit(HPAT).

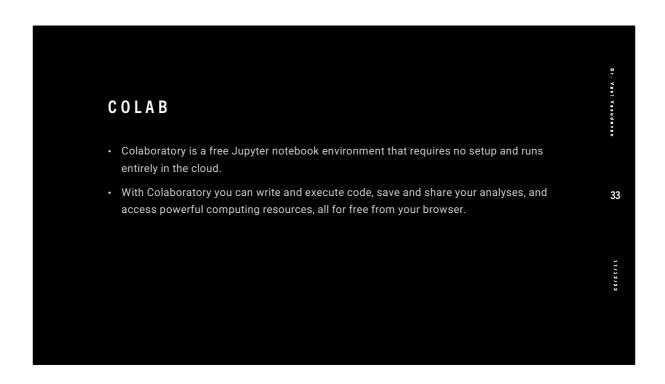
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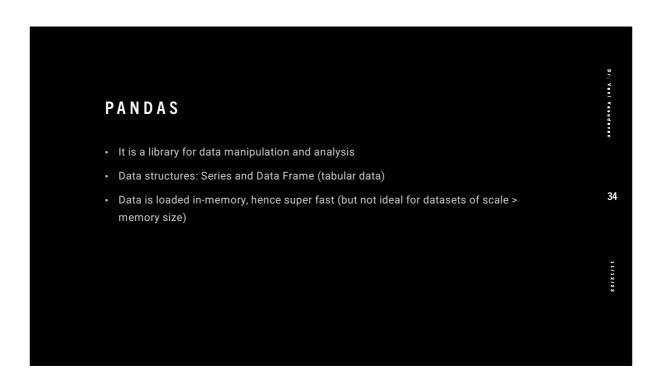


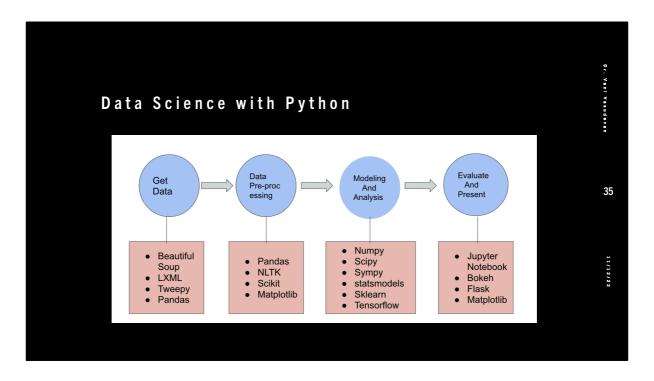






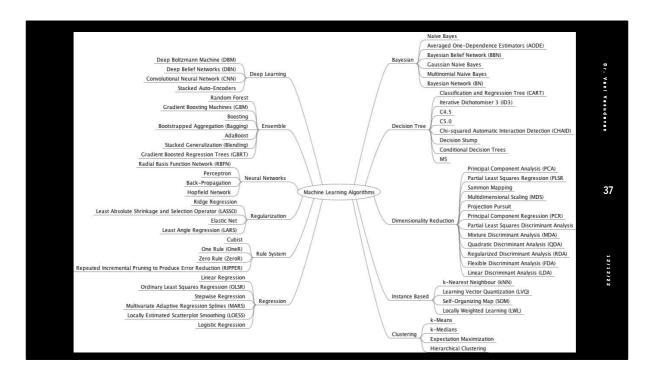






- 1.source: Steven S. Skiena, "The Data Science Design Manual", Springer 2017.
- 2.Data Accquisition --- Beautiful Soup, LXML, Scrapy, Tweepy (Obtaining data by spidering the web etc), pySpark (for large data), mySQL client, mongoDB
- 3.Pre-processing -- Domain Specific Pre-processing techniques (Text: NLTK, Images: Scikit-image etc)
- 4.Analysis/Modeling
  - 1. Exploratory Data Analysis: Pandas
  - 2. Visualization: pylab, matplotlib, seaborn
  - 3. Modeling: numpy, scipy, sympy
  - 4. Hypothesis Testing: scipy, statsmodels
  - 5. Machine Learning: sklearn --
- 5.Evaluation/Interpretation/Communication
  - 1. Latex in Ipython
  - 2. Bokeh
  - 3. Flask

Other Data Science Tools		Dr. Va
WEKA	• RapidMiner	Dr. Vani Vasudevan
R (RStudio)	• Excel	d e v a n
MATLAB	• PowerBI	36
Statistical Analysis System (SAS)	Google Analytics	11/
Apache Hadoop	and much more!	11/12/22
Tableau		
QlikView		



Source: Machine Learning Mastery: <a href="https://machinelearningmastery.com/wp-content/uploads/2021/03/MachineLearningAlgorithms.jpg?\_\_s=hbkixgpvleicleslspeo&utm\_source=drip&utm\_medium=email&utm\_campaign=MMLA+Mini-Course&utm\_content=Machine+Learning+Algorithms+Mind-Map+and+Mini-Course

https://machinelearningmastery.com/parametric-and-nonparametric-machinelearning-algorithms/

### Parametric Approaches:

Logistic Regression Linear Discriminant Analysis Perceptron Naive Bayes Simple Neural Networks

Non Parametric Approaches: k-Nearest Neighbors Decision Trees like CART and C4.5 **Support Vector Machines** 

The research problems in intersection of big data with data science

- Approaches to make the models learn with a smaller number of data samples
- Neural Machine Translation to Local languages
- Handling Data and Model drift for real-world applications
- Handling interpretability of deep learning models in real-time applications
- Building large scale generative based conversational systems
- Building context-sensitive large-scale systems

https://towardsdatascience.com/top-20-latest-research-problems-in-big-data-and-data-science-c6fb51e03136

38

11/12

The research problems related to data engineering aspects

- Lightweight Big Data analytics as a Service
- Auto conversion of algorithms to MapReduce problems

https://towards datascience.com/top-20-latest-research-problems-in-big-data-and-data-science-c6fb51e03136

20

The problems related to core big data area of handling the scale:

- Scalable architectures for parallel data processing
- Handling real-time video analytics in a distributed cloud
- Efficient graph processing at scale

https://towardsdatascience.com/top-20-latest-research-problems-in-big-data-and-data-science-c6fb51e03136

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The research problems to handle noise and uncertainty in the data:

- Identify fake news in near real-time
- Dimensional Reduction approaches for large scale data
- Training / Inference in noisy environments and incomplete data
- Handling uncertainty in big data processing

https://towardsdatascience.com/top-20-latest-research-problems-in-big-data-and-data-science-c6fb51e03136

The research problems in the security and privacy area:

- Anomaly Detection in Very Large-Scale Systems
- Effective anonymization of sensitive fields in the large-scale systems
- Secure federated learning with real-world applications
- Scalable privacy preservation on big data

https://towardsdatascience.com/top-20-latest-research-problems-in-big-data-anddata-science-c6fb51e03136



https://hdsr.mitpress.mit.edu/pub/d9j96ne4/release/3

