Term Paper

For Research Directions

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by

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0.1 Overview of Applied Machine Learning

Applied machine learning is a large topic. It takes the topics and tools of machine learning and theorizes applications for the real-world. The research explores new ways to represent, manipulate, and guide data analysis with machine learning tools. The research often creates new architectures that perform better in an applied scenario. There are many tools within machine learning. Machine learning architecture is also very flexible. For example, each machine learning model can consist of a varing number of layers, nodes, and even submodels. Moreover, machine learning behavior depends on its input. Some of the papers covered in the related work will explore how data manipulations can further the performance of existing machine learning models. For example, it has been shown that providing regularization produces a model that performs better on new data. Furthermore, there are many ways and techniques to apply regularization. Newer theories have proposed new techniques for regularization. Moreover, many of these new techniques may apply to certain types of machine learning architectures or nodes, such as new forms of regularization for LSTM nodes. Of particular interest to my research has included techniques for handling multi-varied types of input. For example, my masters thesis explored the combination of text and image data within a single machine learning model. These types of advanced machine learning pipelines drive big data, big analysis, and ways to analyze complicated data. I plan on continuing to drive my research within the direction of exploring new ways to handle various inputs with different data types. The field of applied machine learning is vast and full of opportunity for new researchers to discover new theories and make innovations in the use, application, and understanding of machine learning.

Examples of popular areas within applied machine learning create theories abou text, audio, image, visual and many other types of data.

applying the topic to real-world problems. Examples of applied machine learning include theories for p

0.2 What area within IT would you like to draw upon to inform a topic that you are interested in?

0.3 Topic

0.3.0.1 What is known about this topic?

0.3.0.2 What needs to be known?

0.3.0.3 What would you like to know?

0.3.0.4 Why is it important?

0.3.0.5 Why we should care?

0.4 Describe your understanding of one or two open problems/questions in IT

0.4.1 What is the gap between what is known and what needs to be known?

0.4.2 What would you like to know?

0.4.3 Formulate a question that specifies b.

0.5 Research Question

0.5.1 Open Research Problems in IT

0.6 Purpose Statement

0.6.1 Signpost that establishes the central intent for the study?

0.6.2 Is there a body of knowledge in IT you would like to contribute to?

0.6.3 Is there an area of practice you would like to improve?

0.7 Theory

0.7.1 Philosophical Assumptions

0.7.1.1 Social Reality

0.7.1.2 What we understand to be true

0.8 How do we understand?

0.9 Means of Investigation

0.9.0.1 Qualitative/Inductive

0.9.0.2 Quantitative/Deductive

0.9.1 Means of Evidence

0.9.1.1 Data Collection

0.9.1.2 Data Analysis

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