CS461 - Artificial Intelligence

HW6

TERRA

Learning with Unsure Responses

Authors

- **Kunihiro Takeoka** NEC Corporation
- **Yuyang Dong** NEC Corporation
- **Masafumi Oyamada** NEC Corporation

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In the process of training machine learning models, the operation of labeling the data is called “data annotation”, and the systems that are responsible for this process are called annotation systems. Although there are many types of data annotation (such as image, text, or entity annotation), all the annotation systems work similarly. “Unsure responses” play a critical role in these annotation systems, and they correspond to a significant portion of the dataset. The current approaches ignore the unsure responses and learn only from the labels that are clearly stated, which leads to an excessive cost and a waste of time. This article provides a solution to make these unsure responses contribute to training classifiers.

In classical approaches, annotators can select the unsure option when they are not confident enough to answer directly as “yes” or “no”. The methodology in these conventional approaches is to ignore the unsure responses to design a machine learning model with certainly labeled instances. However, the paper argues that the “unsure” instances can be used to make the training process more efficient, and instead of ignoring them in building a high-quality model it experiments upon it with a new function. It is observed that these instances can be used to determine the decision boundary which may help to train the model.

A preliminary experiment for the paper indicated that out of the 1425 responses in total that were gathered from 5 different annotators who were asked to classify 400 images on whether they are dogs or wolves, 223 of these responses were labeled as “unsure”. This adds up to 223/1425 = 15.6% of the total responses, which is a significant portion. It is also observed that they are in a close range to the ground truth decision boundary, implying that these instances can have a significant role in the development of a highly qualified supervised machine learning model. The conventional methods suggest that these responses are not of any use and thus they regard them as useless. However, the paper states that these unsure responses can indeed be made use of.

To achieve this, the paper proposes two learning problems and a new loss function called “unsure loss” to work as a regularization to make the decision boundary close to the “unsure” instances. Then it extends the classical methods with the said function and proposes two solutions for the two classification problems. After establishing a valid solution, it puts the new function into experimentation through both synthetic and real-world datasets. After a thorough analysis of the results, it concludes that the new approach is indeed successful, and it outperforms the conventional models in both the synthetic and real-world instances by giving relevant information and statistics on the subject matter. One thing to note is that as the dataset grows larger and as the number of responses grows bigger, the conventional methods start to catch up to the new algorithm yet cannot exceed its efficiency. In other words, the algorithm shows its merits the best on smaller datasets but has no disadvantage over the conventional methods on a larger scale as well, making it a successful algorithm overall.

As artificial intelligence systems start to play bigger roles in our everyday lives, it is no surprise that the algorithms that are used in these systems get more important with every passing day. As the use cases of these algorithms grow larger, the efficiency of them gets more important as well. This article tries to make use of the machine learning models to the upper limit where they start to use the information that is seemingly unimportant at the first glance. The article proposes a solution that is based on enhancing the efficiency of data annotation systems. Since data annotation initiates the process of training a machine learning model and provides what the machine has to

understand and how to distinguish between various inputs to come up with an accurate output, it plays a vital role in AI and machine learning-based models. Machine learning models can make use of the proposed solution to gain a significant advantage over the conventional methods in the long term. Due to the popularization of the said models, the seemingly marginal gains can add up to a point where the recovery of huge chunks of both time and capital resources is much more accessible. Taking all these points into account, as a group, we think that this article is a noteworthy addition to the AI literature, especially for the machine learning related fields.

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