Towards Cloud Computing

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Abstract

Every day, millions of our fellow young young adults spend countless toddler-hours struggling to identify objects from the clouds in the sky, losing out on their childhood years. To this end, we introduce DRIP *for* CLOUT*, a novel benchmark for automated cloud recognition, and we utilize deep learning models to achieve state of the art results on this task. This marks a definitive step towards alleviating the stress of cloud-gazing on toddlers, allowing them to focus on other aspects of life, such as bed-wetting, learning their ABCs, and writing SIGBOVIK papers.*

1. Introduction

In the past decade, there has been a great deal of interest in the adult community in cloud computing [5][6]. This paper is not about that.

Within the toddler community, there has recently been a great deal of interest in cloud computing. During daycare, we are often given a set of toys that over time are increasingly boring and decreasingly sanitary. Thus, we resort to satiate our interests by looking out the windows, longing to explore the wilderness. The closest proxy to such a desire are the ever-changing clouds that loom over the skies, and something that we can stare at all day.

We all know that one of the long standing issues of being a toddler is the inability of identifying clouds. However, in the advent of modern deep learning architectures, we are in a better position to address this complex problem.

In our work, we first introduce the **CLOUT** task (**CL**oud **O**rganization **U**sing **T**oddlers). We then introduce the **Kahoot** data collection paradigm and the **DRIP** (**D**ataset for **R**ecognit**I**on of Cloud **P**atterns), a novel dataset for the **CLOUT** task. Next, we propose several baseline models for the **DRIP** dataset, and provide post-train evaluation metrics on these models. Ultimately, we find that previous researchers could not handle CLOUT because they did not have our DRIP.

2. Related Work

Many toddlers have already made significant research advancements in this field [1]. For example, in [8] researchers have designed an efficient algorithm 1 for identifying clouds, under the supervision of annoying experts, who often refer to themselves as adults:

Algorithm 1 Toddler Forcing

Require: Expert $\mathbf{E}^a$, Toddler $\mathbf{T}^b$, observed cloud **C**
Ensure: Description **D**
  E encourages **T** to describe what they see in **C**
  Init **D** with what **T** thinks it is.
  while D does not have a good description **do**
    E and **T** take turns describing the cloud.
  end while

[a] The Expert is parameterized by an underfitted 100 billion neuron network that maps concepts to semi-grammatically incorrect sentences

[b] The Toddler is parameterized by an untrained 100 billion neuron network that maps concepts to gurgling noises and occasionally grammatically incorrect sentences

Ideally, we would collect our data directly from toddlers, as described in Algorithm 1. However, this is an NP-hard task.[1] In the last year, we have made a major breakthrough with state-of-the-art algorithms, utilizing sweet reinforcement learning (sweet RL) techniques to train toddlers to behave as we want. Using candy such as *Sour Patch Kids* or *Hershey's Chocolate* as the reward, and simulating discounted reward functions by slowly eating the candy[2], we can incentivize the toddler to speak.

Nonetheless, even with these tasty algorithms training toddlers to identify clouds is unreasonably slow and, quite frankly, impractical and inhumane. Thus, we will relinquish such an ambitious goal and resort to using computers, which are much more obedient.

[1] Have you ever tried getting a toddler to do what you actually wanted them to do?

[2] Effectively stealing candy from a baby

	Kahoot	Socratic Seminar	Raising Hands	Owl	4chan
Virtual	✓	✗	✗	✗	✓
Latency (ms)	10	1000	5000	600000000	10000
Used in education	✓	✓	✓	✓	✓
Engaging Music	✓	✗	✗	✗	✗
Contains “K” in name	✓	✗	✗	✗	✗
Custom Username	✓	✗	✗	✓	✓
Used by Wizards	✗	✗	✗	✓	✗
Non-GMO	✗	✗	✗	✓	✗
Shames failure	✓	✗	✗	✗	✓
Onii-chan	✗	✗	✗	✗	✓
Hotel?	Trivago	Trivago	Trivago	Trivago	Trivago

Table 1: Comparison of Data Collection Paradigms. Our Kahoot paradigm is most robust, followed by Owl.

3. The CLOUT Task

We now introduce the main objective of this paper, the CLOUT problem: *Given a labeled dataset* $D = \{(x^{(i)}, y^{(i)})\}_{i=1}^{N}$, *train a deep network classifier to best approximate the target function* $f : X \to y$, *mapping cloud instances to their labels.*

4. The DRIP Dataset

As directly sampling from toddlers is computationally infeasible (and possibly illegal?), we approximate the mind of a toddler by collecting data from undergraduate computer science students, which has repeatedly been shown to be an asymptotically tight approximation [3]. Following this method, we acquire DRIP.

4.1. Cloud Image Source

We obtain our images from the Singapore Whole Sky IMaging SEGmentation Database (SWIMSEG), a dataset of 1013 images originally labeled for cloud segmentation [4].

Below are 4 sample images, one from each of the 4 classes:

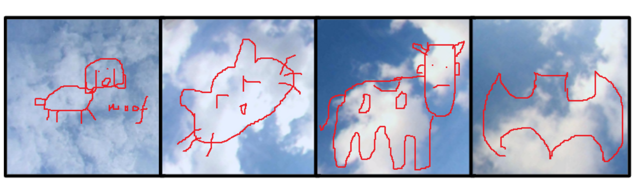

Figure 1: Sample Images from SWIMSEG, with labels (from left to right) dog, cat, cow, and bat

[3]For example, `https://www.instagram.com/cmudaddythicc/?hl=en`

4.2. Kahoot Data Collection Paradigm

As data collection was conducted during the pandemic, we needed to obey the social distancing L_∞ metric. As such, we designed the Kahoot Data Collection Paradigm, which allowed our undergraduate subjects to participate remotely. The students helped us label images with 4 classes, namely *bat*, *cat*, *cow*, and *dog*. Additionally, students are familiar with this platform, and also have the flexible choice to anonymize their names if they so choose.

Further, to appease undergraduate students seeking a career in research, we offered as an additional incentive to credit them as coauthors on this paper. However, we never *pinky-promised*, and as such their names remain conspicuously absent.

To demonstrate the effectiveness of our choice, we display the comparison table of other data collection paradigms in table 1.

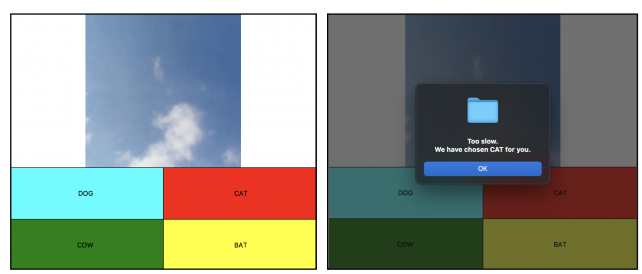

Figure 2: **Left:** Kahoot data collection setup. **Right:** After ten seconds, Kahoot times out and selects an answer for the user.

4.3. Data Quality

We leave an exploration of data quality to future work. We assure the reader that data quality is by far one of the goals of this work.

4.4. Comparison to Existing Datasets

We present in Table 2 a comparison between DRIP and related cloud computing datasets. Unfortunately prior to this work, we did not know adults also used the term "cloud computing." As such we were fooled into running preliminary experiments on Google and Microsoft Azure's knockoff datasets for what they consider to be "cloud computing."

	DRIP	IN	GC	AP
Has clouds	✓	✓	✗	✗
Used for cloud computing	✓	✗	✓	✓
Introduced by this paper	✓	✗	✗	✗
Random labels	✓	✗	✗	✗

Table 2: DrippingCap, a comparison of DRIP against related cloud computing datasets, ImageNet (IN), Google Cluster Dataset (GC), and Azure Public Dataset (AP)

5. Models

A great deal of recent work in machine learning and adjacent fields has focused on eliminating biases from datasets and models. Specifically, there has been much work towards preventing models from learning harmful biases against certain groups. In this paper, we extend this by preventing our model from learning anything at all. In an effort to accomplish this, we propose *extreme* label smoothing (XLS).

Label smoothing [7] modifies the label distribution by interpolating with some $\epsilon \in [0, 1)$ between the true one-hot label distribution $q(k \mid x)$ and a uniform prior $u(k)$:

$$q'(k \mid x) = (1 - \epsilon)q(k \mid x) + \epsilon u(k) \quad (1)$$

This naive (and frankly discriminatory approach) leaves much room for the model to learn undesirable associations from the data - for example, that cows are fatter than dogs. Hence, in extreme label smoothing, we propose to set $\epsilon = 1$ in Equation (1). Where label smoothing penalizes overconfidence, extreme label smoothing destroys the model's self-confidence altogether. Machine learning can't bully us if we bully it first.

Ultimately, rather than training a discriminator, we wish to train a unifier that brings all classes together in Marxist harmony [2].

6. Experimental Evaluation

Our accuracy is very good, trivial by Jensen's [4].

[4]Source: `https://www.youtube.com/watch?v=-fGKrYq8_dk`

7. Results and Discussion

Surprisingly, the confusion matrix for all of our experiments were the same, shown in figure 3.

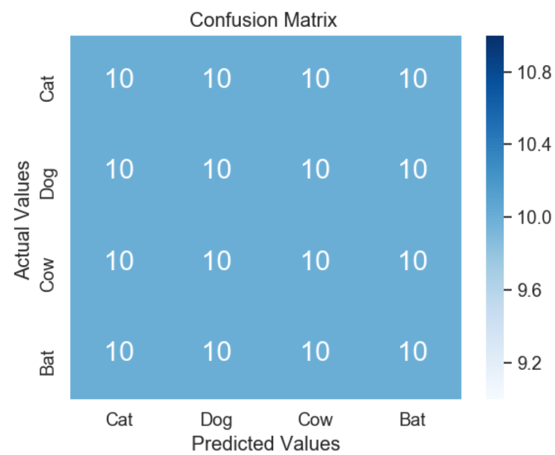

Figure 3: Confusion Matrix of our experiments

This can be attributed to the fact that our research assistants were toddlers who only had ten fingers with which to record results. We hope that in the future, we can get more fine-grained results by having our researchers use their toes as well.

8. Conclusion

We conclude that our state-of-the-art machinery is able to predict the shape of clouds extremely accurately, thus we toddlers are bing chilling [3].

9. Future Work

We have solved the millennium problem of identifying clouds. We expect toddler researchers to be very happy because they can now move onto other research challenges, such as estimating the rate of grass growth and the rate of bed-wetting.

10. Acknowledgements

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