On the contribution evaluation and credit distribution of a data labelling framework

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This paper presents a credit assignment framework of the Vulcan Coalition labelling platform.

1 Introduction

Data labelling is a process from which training data for supervised learning are prepared (Russell and Norvig, 2002). It usually involves manually annotate data by expert workforce that expects some form of compensation or credits. The simplest scenario is to backwardly assign credits after the labelling results have been evaluated and successfully generated actual credits. This is not realizable from the aspect of economics however, where incentives are usually promised before the actual tasks can be performed. Besides, results that yield low evaluation score or cannot produce tangible credits at a time may produce higher yields latter on when opportunities arise.

Due to the uncertainty of the future, the credit assignment problem turns out to be one of the hardest problems for which we struggle to attain the optimal solutions. Though limited successes are achieved only through constraints and strong assumptions (Minsky, 1961; Gittins, Glazebrook, and Weber, 2011).

In this paper, we propose a study of the credit assignment problem and a solution employed within the Vulcan Coalition data labelling framework [1]. Our primary goal is to attribute work credits after and before the labelling results are achieved in order to feedback, motivate, and provide pre-work incentives for the labeller workforce (which we will refer to as users). Due to this end, we divide the problem of credit assignment into two sub problems: contribution evaluation and incentive computation; while the former convenes methods to evaluate the labelling results, the latter focuses on how to set up promised rewards based on available information. We give both of the sub-problems equal credits, though in future this can be adjusted to better balance evaluation accuracy and better incentive in order to achieve maximum benefits from the labelled data.

[1] https://www.vulcancoalition.com

2 Contribution evaluation

Vulcan Coalition uses the labelled data to generate profits by developing machine learning models. We can compute the exact hindsight rewards from the developed models using sensitivity analysis methods (Saltelli, 2002; Saltelli et al., 2008; Xia et al., 2020). These methods utilize the effect of the first order analysis of the inputs on the outputs of the models.

However, there are sometimes cases where we want to evaluate the reward credits beforehand, such as interval workforce performance check and quality control or releasing the labelling data themselves for public use. When external business factors initiate the evaluation computation process, we score the contribution using the following data qualification techniques: a) gold standard comparison b) population deviation

2.1 Gold standard comparison

Given a set of preferred labels for each task (or job interchangeably), we directly compare the user labelling results to these so-called ground truth in order to measure similarity. The higher the similarity score, the higher the credits that user will receive.

Each labelling task category has its own label metrics that must be defined. Algebraically, this is the same as to define a subtraction and a norm operation on the set of task label representation.

2.2 Population deviation

Without a set of preferred labels, we can still evaluate user performance through the measure of deviation from the population norm. The population norm can be mean, median, or any statistical representation of the collective labeling results from the platform user groups.

Apart from a subtraction and a norm operation, an aggregation and a scalar operation must be defined. This constitutes a normed vector space for any labelling category.

3 Incentive computation

Before the users select labelling jobs to perform, they are presented with the promised benefit of each job as the incentive. This incentive computation constitutes the second half of the user credit assignment process.

To compute proper incentives, our framework considers 1. the estimated value of each job 2. user count in each group, which we will refer to as workforce 3. eligibility of each workforce group performing each job 4. job workforce count requirements from business contracts 5. and labelling platform availability . Roughly, a user should select to perform a job based on its values per time yield; the higher the better. It is therefore straightforward to use this as the base for the incentive. To compute it, we define utility score as the sum of the estimated value per time over all workforces assigned to jobs. We frame an optimization problem to find a workforce assignment that maximizes the utility score across all workforce groups and all jobs, while trying to satisfy all workforce count requirements. (See Table 1 for notations.)

$$
\begin{aligned}
\max\ & V^{\intercal}\mathbf{A}\vec{1} & \\
\text{subject to}\quad & \mathbf{A}\vec{1} & \geq R \\
& \mathbf{A} & \geq 0 \\
& \mathbf{A}^{\intercal}\vec{1} & = W \\
& a_{jw}(1-e_{jw}) = 0 &
\end{aligned}
$$

The workforce assignment A is not a hard constraint. Each individual user in a workforce group can work on any jobs that they are eligible for. The job workforce incentive is a factor that helps users in each workforce group to select jobs based on their expected profits.

$$c_{jw} \propto \frac{a_{jw}}{\max_j a_{jw}}$$

The incentive is a monotonically increasing function of the normalized workforce requirement for each job. We propose an S-curve shape function, assuming that people's incentive is based on a trigger threshold point with a saturating.

Given the job workforce incentive, each user can freely choose which job to perform based on individual affinity. The user incentives are set based on to which workforce group that each user belongs, at the time of labelling. Further, each labelling job has different unit system for amount, we need to compute job average user speed to convert users' units of work into the unit of time. And finally the credits reward for each user is then computed after we retrieve the total units of work that each user produce over a period of time:

$$\text{reward}_u = \sum_j c_{ju} p_{ju} s_j^{-1}$$

4 Summary

This paper presents a credit assignment framework of the Vulcan Coalition labelling platform.

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Table 1: *Glossary of mathematical notations*

Name	Description	Representation	Notation
Job total count		$\mathbb{N}$	$\lvert\mathbf{J}\rvert$
Workforce total count		$\mathbb{N}$	$\lvert\mathbf{W}\rvert$
Summer	A constant vector of all ones	$1^{\mathbb{N}}$	$\vec{1}$
Job values	Job's value per time	$\mathbb{R}^{+\lvert\mathbf{J}\rvert}$	V
Job requirement	Job minimum workforce requirement	$\mathbb{N}^{\lvert\mathbf{J}\rvert}$	R
Workforce count	Workforce count in the pool	$\mathbb{N}^{\lvert\mathbf{W}\rvert}$	W
Workforce eligibility	Workforce w eligibility for job j	$\{0, 1\}$	e_{jw}
Workforce-job eligibility	All workforce eligibility	$e^{\lvert\mathbf{J}\rvert\times\lvert\mathbf{W}\rvert}$	$\mathbf{E}$
Workforce assignment	Number of workforce w assigned to job j	$\mathbb{N}$	a_{jw}
Workforce-job assignment	All workforce assignment	$a^{\lvert\mathbf{J}\rvert\times\lvert\mathbf{W}\rvert}$	$\mathbf{A}$
Job workforce incentive	Job j incentive for workforce w	$\mathbb{R}^{+}$	c_{jw}
Job user incentive	Job j incentive for user u	c_{jw} where $u \in w$	c_{ju}
Job speed	Average units of work produced per time for job j	$\mathbb{R}^{+}$	s_j
Job produced	Sum of units of work produced on job j for user u during a measurement interval	$\mathbb{R}^{+}$	p_{ju}

$u \in w$ means user u is a member of workforce w; e.g., u belongs to the blind group. This is a strictly many to one relationship.