Towards Automatic Low Hanging Fruit Identification For the Steering of ML Research

Nick Frosst, Aidan Gomez

February 2019

Abstract

In light of the ongoing explosion of interest in the field of machine learning, we must ask ourselves how researchers can best allocate their resources and determine which problems deserve their attention. We identify and explore the perennial problem of low hanging fruit detection in machine learning research organizations and present a novel, state-of-the-art AI solution to this pertinent problem, which we believe will greatly increase the output of research papers in the machine learning community.

1 Introduction

The field of machine learning is undergoing a period of rapid and accelerating growth. The commercial viability of recent research developments and the public notoriety thereby achieved, has lead to the establishment of several large scale academic institutions devoted to the development of artificial intelligence through machine learning. Moreover, many commercial entities have started to fund purely research focused machine learning groups. This has lead to a period of rapid progress, made possible by the cross institutional collaboration of researchers and the public forums in which they share their work. This veritable renaissance of *artificial intelligence* however comes with a downside; it is increasingly difficult to stand out among the growing field of stellar researchers and fruit enthusiasts. It would appear that as a consequence of the rapid and sustained growth in our field, many have become increasingly concerned about the supply of low-hanging fruit. This paper presents a novel solution to this problem in the form of a state of the art Low Hanging Fruit Detection model. Our model is able to accurately identify the lowest hanging fruit and subsequently orient the research objectives of this new cornucopia of research entities.

2 Prior Work

Much effort has been put into the identification of low hanging fruit (for details, please see all machine learning papers published in the past 3 years with citation

Figure 1: Low hanging fruit detection has been a concern for humanity throughout the ages. Our modern times however, have made this problem all the more pertinent. It is of no coincidence then that it is with modern technology that a solution can be found.

numbers exceeding 234, excluding those written by the authors of this paper, we do good work, and that one about the dancing [1], that was top quality stuff). Yet little has been done on approaching this important problem from an algorithmic perspective. The potential for automated low hanging fruit detection to give researchers the opportunity to focus on problems that take way more time and are just kind of hard and tiring to work on, is enormous.

Furthermore, there is an abundance of research papers devoted to the subject of autonomous orchard management and the various fruit related machine learning problems therein [4, 3, 2, 5]. Many of these papers were long, and complicated, and so we leave reading them and determining their relevance as an exercise to the reader.

3 Data

In order to train such a system, we first needed to collect a dataset of low hanging fruit and high hanging fruit. Our initial strategy was to create a web crawler of machine learning arXiv submissions to collect the abstracts of papers submitted within the past 3 years. We were to label all those authored by individuals with papers per year in excess of 3 as low hanging, and the rest as high hanging fruit. We would then train a classifier on this dataset, present the findings here in this paper, and reap the rewards. After careful examination we decided that this approach was too hard, and achieving state of the art results may actually require a fair bit of work. With this in mind, we focused our attention on real fruit instead. We collected a dataset of images of apple orchards and drew bounded boxes around the lowest fruit in each image. We figured that training a model to identify the bounding box of the lowest hanging fruit in each image would be sufficient for a workshop paper at least.

4 Method

We trained a simple CNN with methods mostly established in the early 2010's on all the data we could find, This resulted in state of the art scores for the low hanging fruit detection task which we had just established. We benchmarked our model against randomly labeling things. Our model greatly outperformed this baseline. Having achieved state of the art results, we found no need to further refine our approach or explore any other alternatives.

Figure 2: Our research team did some field work to understand the nature of the problem. Here we have pictured our research collaborator grasping for obviously not low hanging fruit. Why is she doing?

5 Grasping The Fruit

Our model is able to accurately detect low hanging fruit in orchard related images, but the standard CNN alone is only able to identify the position of the low hanging fruit, not grasp the fruit once it has been located. Augmenting our approach to enable such capabilities would result in an end-to-end fully learned and deployable low hanging fruit production pipeline. This development would be indispensable to the machine learning community. With this in mind, we created a model relying on the most recent cutting edge ML developments, using RL to train a robotic fruit grasping hand, and stacked invertible residual neural ODEs to draw bounding boxes around the fruit. We did not actually train this model, as it was not particularly easy to do. We leave it instead as a fruitful area of future research, but do note to future researchers that this flag was planted here first, which means you need to cite us.

6 Discussion

In the interest of public safety, and in light of recent trends, we have decided not to release any code or model checkpoints, or results for that matter; our low hanging fruit model is simply too powerful. We would also like to take this time to announce a new private for profit spin-off of our research and welcome any VC investment in our seed funding round.

7 Conclusion

We have presented a novel approach to the perennial problem of low hanging fruit detection. Our model achieves state of the art performance on the low hanging fruit detection data set which we have created. We believe this model will be an indispensable tool to guide the research objectives of the ever increasing onslaught of ML research institutions. We have decided not to release the trained model parameters or any code at all actually, over public safety concerns, i guess.

References

[1] Caroline Chan, Shiry Ginosar, Tinghui Zhou, and Alexei A Efros. Everybody dance now. *arXiv preprint arXiv:1808.07371*, 2018.

[2] A Gongal, Suraj Amatya, Manoj Karkee, Q Zhang, and Karen Lewis. Sensors and systems for fruit detection and localization: A review. *Computers and Electronics in Agriculture*, 116:8–19, 2015.

[3] Keren Kapach, Ehud Barnea, Rotem Mairon, Yael Edan, and Ohad Ben-Shahar. Computer vision for fruit harvesting robots–state of the art and challenges ahead. *International Journal of Computational Vision and Robotics*, 3(1/2):4–34, 2012.

[4] Tianhao Zhang, Zoe McCarthy, Owen Jowl, Dennis Lee, Xi Chen, Ken Goldberg, and Pieter Abbeel. Deep imitation learning for complex manipulation tasks from virtual reality teleoperation. In *2018 IEEE International Conference on Robotics and Automation (ICRA)*, pages 1–8. IEEE, 2018.

[5] Andrejs Zujevs, Vitalijs Osadcuks, and Peter Ahrendt. Trends in robotic sensor technologies for fruit harvesting: 2010-2015. *Procedia Computer Science*, 77:227–233, 2015.