Multi-Criteria Evaluation of Publication Impacts: Deep Learning in Autonomous Vehicles

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***Abstract*—Deep learning is the state-of-the-art approach that has been extensively used in the recent years to variety of real-world problems in the literature. The autonomous vehicles are among the applications where their integration with deep learning techniques has potential to disruptively change our daily lives. In this work, we have proposed a multi-criteria framework to evaluate the relative impacts of both publications and authors for deep learning in autonomous vehicles. For the framework, we have considered several criteria extracted from the metadata of the publications and the authors. The conflicts among the criteria are also justified through Pearson correlation. For the experiments, two comprehensive datasets for the publication and the author impacts have been constructed. The resulting pareto-fronts of the datasets after ranking are presented. Moreover, top 30 most impactful publications and authors in the literature are identified. We hope that our findings will be useful for researchers to accelerate the further technological advancements.**

I. Introduction

Deep learning is a subset of machine learning family with multi-layered multi-neuronal architecture [1], [2]. It has been developed through the inspiration of the structural and functional attributes of brain which is among the most powerful problem solvers in the nature. Through the series of connected layers, it basically aims to transform the data into more abstract and composite representation in order to perform complex tasks. Deep learning has been shown to have highly accurate predictive and generative capabilities [3]. Therefore, it has been applied into variety of application domains over the recent years including autonomous vehicles [4], computer vision [5], drug discovery [6] and cloud computing [7].

Autonomous vehicles in the literature refer to self-driving transportation systems with no or minimal human intervention. In general, autonomous vehicles consist of three major modules for perception, decision and control that harmoniously work to substitute for drivers [8]. However, they require very complex tasks to be efficiently performed for driving safety and operability. Deep learning is among the techniques which has been successfully integrated with autonomous vehicles. The work [4] proposes hybrid system based on convolutional neural networks and support vector machines for pedestrian recognition and detection. Similarly, the work [9] constructs comprehensive dataset for highway driving and applies deep learning along with computer vision for car and lane detection. Another work [10] presents end-to-end deep learning framework for autonomous vehicles by considering spatial and temporal aggregation at the same time.

The multi-criteria evaluation of the publication impacts has been rarely studied in the literature. To the best of our knowledge, only the work [11] introduced a method as Pareto-Vikor (P-V) to relatively assess the publication impacts of the authors from the literature. The method basically uses pareto-domination and multi-criteria decision making measure to obtain the complete order between the authors. However, it suffers from certain drawbacks needed to be addressed for better performance. Firstly, it is not comprehensive with respect to number of the authors considered. Secondly, it examines only h-index and research period without stating the underlying motivation and systematically justifying their conflict. In our work, we have considered different criteria including citation, centrality and i10-index in addition to the h-index and the research period. Furthermore, we separately investigate the publication impacts along with the author impacts. Another difference is that while the paper [11] takes the evolutionary computation into the account, we consider deep learning in autonomous vehicles in our work. The scientific community can benefit from our proposed framework and findings to accelerate the technological advancements and education.

The main contributions of this paper is as follows:

- We have proposed a multi-criteria evaluation framework based on pareto-domination strategy to assess the impacts of the publications and the authors.
- We have constructed two separate comprehensive datasets including the publications and the authors for deep learning in autonomous vehicles.
- We have considered different criteria for both datasets and justified the conflicts among the criteria through Pearson correlation.
- We have identified top 30 most impactful publications and top 30 most impactful authors for the current literature along with their pareto-fronts.

The remainder of the paper is organized as follows. Section 2 describes our research methodology for paper selection. Section 3 overviews the multi-objective optimization and the non-dominated sorting in our multi-criteria evaluation framework. Section 4 explains the datasets and the criteria of the framework for the publication and the author impacts. While Section 5 presents the results, Section 6 concludes the paper.

II. Research Methodology

A. Search Criteria

The publication selection for the datasets has two sequential phases as querying the digital libraries and scanning the reference sections of the publications already collected. In the first phase, our search criteria have been formulated through a search query that is executed on the digital libraries. We have separately inspected the most commonly used keywords of two domains as deep learning and autonomous vehicles in the literature. The keywords in the same domains are merged with logical disjunction operator (i.e. OR) while the keywords in the different domains are merged with logical conjunction operator (i.e. AND). The resulting search query is as follows:

> (”deep learning” OR ”deep neural network” OR ”deep reinforcement learning” OR ”deep convolutional network”) AND (”autonomous driving” OR ”autonomous vehicles” OR ”intelligent driving” OR ”intelligent vehicles”)

In the second phase, the reference section of each publication collected has been manually scanned. It should be noted that this improves the comprehensibility of our dataset to a great extent. It also helps to build larger and more connected publication and author citation graphs.

B. Information Sources

The digital scientific databases have been used as information source where our search query is executed to collect the set of only relevant publications. The main goal is to obtain workshop proceedings, conference proceedings, journals, surveys and preprinted articles. The timespan of the publications collected starts from the early stages of deep learning in autonomous vehicles in the literature until the end of 2020. The popularly used four digital databases that have been covered in this work are as follows:

- Google Scholar (https://scholar.google.com)
- IEEE eXplore (https://ieeexplore.ieee.org)
- ScienceDirect-Elsevier (https://sciencedirect.com)
- ACM Digital Library (https://dl.acm.org)

C. Inclusion/Exclusion Criteria

After the execution of the search query in the digital databases and the manual reference scanning, we have obtained the potential papers from the literature. Although we have eliminated a part of irrelevant papers through the search query, there have been still some irrelevant papers due to the conflict between the keywords. Therefore, we have consecutively applied additional elimination steps where we have checked their headings, abstracts and full texts based on our research goals. For that purpose, our inclusion criteria can be listed as follows:

- The publications must contribute to the main focus of our work as deep learning in autonomous vehicles at least from one aspect.
- The publications must be written in English where the quality standards of non-English papers are disputable.
- The publication dates must be from the inception of the related literature until 2020 to equally cover the history of the publications and the authors.
- The publications could be published in peer-reviewed workshop proceedings, conference proceedings and journals along with preprinted venues.

The consideration of the preprints is important since the adoption of the preprints has been increasingly growing among the researchers for fast-changing domains over the recent years. At present, there are examples of works considering the preprints for review [12]. Our exclusion criteria can be simply defined as the opposite of our inclusion criteria. Note that the selections of our inclusion and exclusion criteria are based on the recommendations from the work [13]. The implementation of the inclusion and the exclusion criteria over all the potential publications results in 731 publications and 1242 authors at the end. The distribution of the selected papers into their publication years is provided in Fig. 1.

III. Background

A. Multi-Objective Optimization

The multi-objective optimization involves with the minimization or the maximization of multiple conflicting objectives at the same time under various constraints. Without loss of generality, the multi-objective optimization can be defined as:

$$\begin{aligned} \text{Maximize/Minimize } & F(x) = (F_1(x), F_2(x), ..., F_f(x))^T \\ \text{such that } & g_j(x) \geq 0, j = 0, 1, ..., J \\ & h_k(x) = 0, k = 0, 1, ..., K \end{aligned}$$

where $x = (x_1, ..., x_n)^T \in X$ is the vector of decision variables, $F : x \rightarrow R^f$ is the set of different objectives to be optimized, g in eq. (2) is the inequality constraints and h in eq. (3) is the equality constraints. The solution vectors consisted of decision variables form the *decision space* X. Likewise, the objective function values of the solution vectors form the *objective space* Z [14].

The presence of multiple objectives leads to trade-offs which should be evaluated by more different approaches than the ones for single-objective optimization. The most commonly used approach is a partial ordering mechanism called as *pareto-domination*. For two solution vectors as x and y, the solution x dominates the other solution y if the solution x is at least equal to the solution y for all objectives in the objective space and the solution x is strictly better than the solution y for at least one objective. It can be mathematically formulated as follows for minimization:

$$\forall i : F_i(x) <= F_i(y) \wedge \exists j : F_j(x) < F_j(y) \quad (1)$$

where $F_i(x)$ and $F_j(x)$ denote the values for ith and jth objective functions for the solution x, respectively; and similarly, $F_i(y)$ and $F_j(y)$ denote the values for ith and jth objective functions for the solution y, respectively.

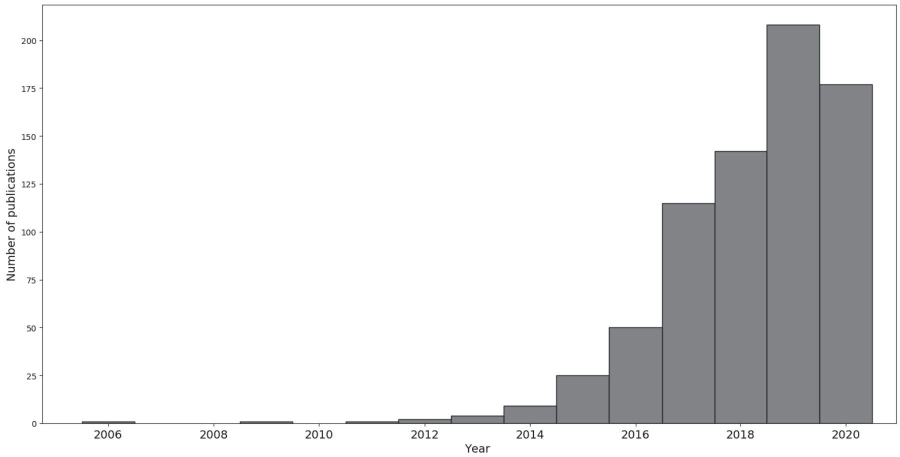

Fig. 1. The distribution of the number of publications over the years

A solution x^* is called as *non-dominated* or *pareto-optimal* if there is no solution among all the solutions that dominates it. The main difference between single-objective and multi-objective optimizations is that there may exist multiple pareto-optimal solutions in multi-objective optimization. The set of all pareto-optimal solutions form a trade-off as *pareto-optimal set (POS)* (i.e. $POS = \{x^* \mid x^* \in X\}$) in the decision space and *pareto-optimal front (POF)* (i.e. $POF = \{F(x) \mid x \in POS\}$) in the objective space [15].

B. Fast Non-dominated Sorting

Although pareto-domination is a reliable pairwise comparator between two different solutions, it is not sufficient alone to provide complete orderings among all solutions. For that purpose, the *fast non-dominated sorting* mechanism from the NSGA-II algorithm [16] has been extensively used in the literature. It is more advanced version of NSGA [17] where the computational costs of sorting is alleviated. The NSGA-II algorithm classifies the solutions into different ranks with respect to their non-domination levels. It stores two attributes of each solution as the domination count which denotes the number of solutions dominating that solution and the domination set which denotes the set of solutions that is dominated by that solution. First, the solutions with domination count of zero are considered as the first rank. Then, the domination counts of the solutions in the domination sets of the solutions in the first rank are reduced by one. The solutions with the resulting domination count of zero are considered as the second rank. This goes on until all the ranks are fully identified.

It is possible to have more than one solutions in each rank after the fast non-dominated sorting. Therefore, an extra effort is necessary in order to sort the solutions in the same ranks. The issue has been addressed through the *crowding distance* mechanism in the NSGA-II algorithm based on the Manhattan distance of two neighbouring solutions [16]. This mechanism requires the solutions to be sorted for each objective where the boundary solutions are assigned to infinity. The other solutions are assigned to the sum of the absolute normalized distance of two neighbouring solutions for all the objectives. Based on fast non-dominated sorting and crowding distance, the solution x is preferred over the solution y if and only if:

$$(x^{rank} < y^{rank}) \vee (x^{rank} = y^{rank} \wedge x^{cdist} > y^{cdist}) \quad (2)$$

where x^{rank} and y^{rank} denote the ranks of the solution x and y, respectively; and similarly, x^{cdist} and y^{cdist} denote the crowding distances of the solution x and y, respectively. Note that the solutions in the lower ranks are more favoured for the first case and the solutions in less densely populated regions are more favoured for the second case.

IV. Multi-Criteria Evaluation Frameworks for Publication and Author Impacts

A. Datasets

The datasets for the publication and the author impacts have been constructed through metadata of the selected publications and the authors of those publications, respectively. They are comprehensive for deep learning in autonomous vehicles with 731 different publications and 1242 different authors. The publication metadata includes the name, the publication year, number of citations and the authors of the publication queried. The oldest publication in the dataset is "Off-road obstacle avoidance through end-to-end learning" [18] published in 2006 with 6-layer convolutional neural networks for autonomous off-road vehicles. Similarly, the most cited publication in the dataset is "Image-to-image translation with conditional adversarial networks" [19] with 8255 citations while there are many publications with no citation.

The authors to be considered in the dataset must have one publication at least for deep learning in autonomous vehicles and must have valid Google Scholar profiles. The author metadata includes the name, identification number, affiliation, research interests, the number of yearly and total citations, the number of total h-index and the number of total i10-index of the author queried. The author with the most research duration of 37 years is Alberto Sangiovanni Vincentelli from University

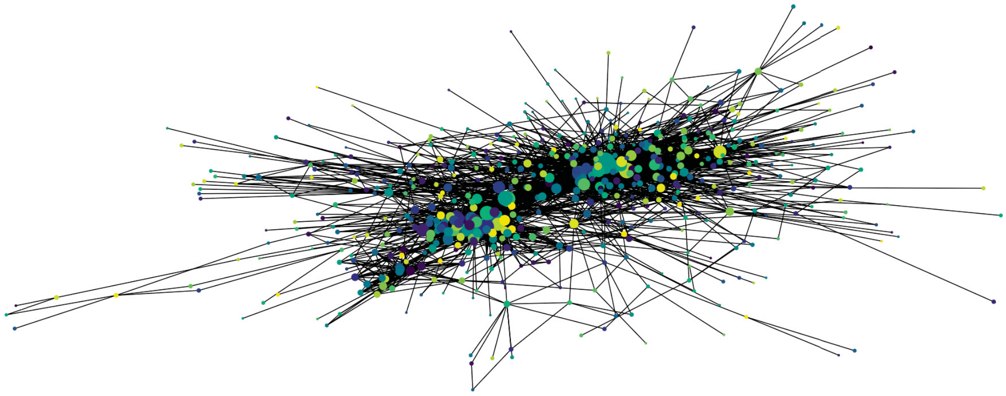

Fig. 2. The citation graph for publication dataset

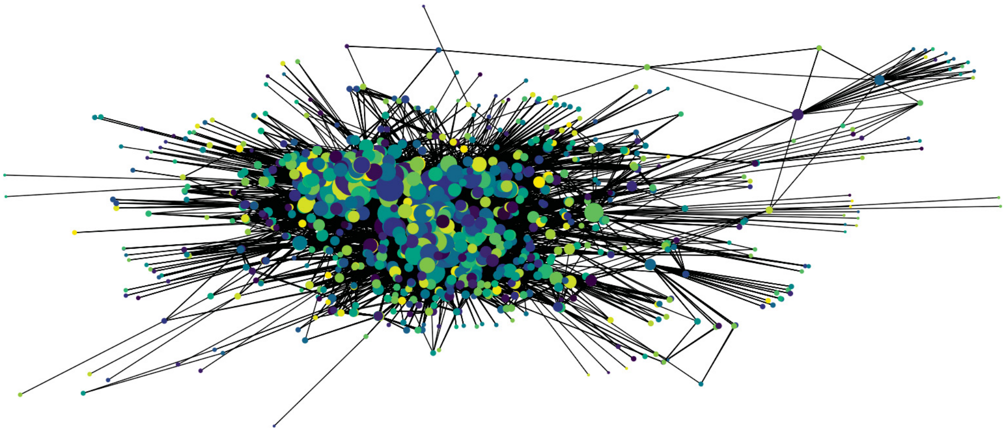

Fig. 3. The citation graph for author dataset

of California. The authors with the highest citation of 188204 is Yann LeCun from Facebook, with the highest h-index of 154 is Luc Van Gool from ETH Zurich and with the highest i10-index of 969 is Fei-Yue Wang from Chinese Academy of Sciences. Finally, the author with the highest number of publications of 8 in our dataset is Xiaogang Wang from The Chinese University of Hong Kong.

B. Criteria

The criteria employed for our multi-criteria evaluation are presented in this section. The criteria including citation, duration and centrality are used for both publications and authors; h-index and i10-index are used for only authors; and finally average author citation, average author h-index and average author i10-index are used for only publications. They are integrated with our framework through fast non-dominated sorting and crowding distance to evaluate the impacts of the publications and the authors in the literature.

1) Citation (Publication / Author): A citation is a reference to formerly published publication from where certain knowledge is obtained. It has been extensively used to measure the scientific impact of a publication or an author. However, there are certain drawbacks to solely use citation as an impact indicator. Firstly, it is vulnerable to be intentionally misused through extreme self-citation or implicit citation [20]. The work [21] published publicly available dataset to reveal interesting facts about self-citations of the researchers in different fields. Secondly, there is correlation between the number of citations a publication or an author receives and the time factor.

2) Duration (Publication / Author): It shows the amount of years a publication is published or an author has been actively publishing, spanning from the earliest publication to the latest publication. The authors with good quality of publications with respect to other criteria within shorter duration are more favoured in our multi-criteria evaluation framework.

3) Centrality (Publication / Author): Two citation graphs for the publications and the authors have been separately constructed where each vertex is a publication or an author, respectively, while each edge is citation relation from a publication or an author to another one it cites, respectively. For each vertex in the graphs, betweenness centrality score is calculated, which measures the significance of a vertex by the number of the shortest paths leading through it [22], [23]:

$$bc(v) = \sum_{s,t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{3}$$

where v, s and t are different vertices, $\sigma_{st}(v)$ is the number

TABLE I. THE CORRELATION VALUES AMONG CRITERIA FOR PUBLICATION IMPACTS

	Citation	Duration	Centrality	Avg. Citation	Avg. h-index	Avg. i10-index
Citation		0.23 (2.e-10)	0.38 (7e-27)	0.17 (2e-6)	0.1 (5e-3)	0.03 (3e-1)
Duration			0.09 (1e-1)	0.32 (7e-20)	0.26 (1e-13)	0.13 (1e-4)
Centrality				0.05 (2e-1)	0.03 (3e-1)	0.01 (9e-1)
Avg. Citation					0.76 (4e-140)	0.65 (8e-90)
Avg. h-index						0.85 (2e-209)

TABLE II. THE CORRELATION VALUES AMONG CRITERIA FOR AUTHOR IMPACTS

	Citation	Duration	Centrality	h-index	i10-index
Citation		0.38 (1e-42)	0.1 (2e-4)	0.77 (1e-238)	0.68 (2e-170)
Duration			-0.01 (9e-1)	0.66 (2e-156)	0.55 (1e-99)
Centrality				0.05 (4e-2)	0.03 (3e-1)
h-index					0.87 (0.0)

of shortest from vertex s to vertex t through vertex v and σ_{st} is the number of shortest from vertex s to vertex t. The vertices with high betweenness centrality have more impacts over the other vertices in the graph. The citation graphs for the publication and the author datasets are shown in Fig. 2 and Fig. 3, respectively.

4) h-index (Author): The h-index of an author represents the number of publication of that author with at least h citations for each [24]. It has been shown as promising metric for author quality by avoiding the disadvantages of the existing metrics in the literature [25]. The h-index can be misleading in certain circumstances since although high h-index is an indicator of high quality author, the converse is not always true.

5) i10-index (Author): The main disadvantage of total number of publications is that it does not indicate the impacts of the publications although it measures the productivity of an author. For that reason, i10-index is defined as simple metric to consider the number of publications of an author with at least 10 citations [26].

6) Average author citation, h-index and i10-index (Publication): They are defined as average of citations, h-index and i10-index of the authors participating in the same publication. Although the true scientific impact of a publication cannot be single-handedly measured through these criteria, it is more likely for a publication with highly cited authors to have high impact in the community. Note that the citations, h-index or i10-index of the authors without valid Google Scholar profiles are not taken into the consideration during the calculations.

V. RESULTS AND DISCUSSION

A. Correlations between Criteria

The correlation analysis between different criteria is studied in order to reveal their dependencies and simplify the representation of the objective space [27], [28]. Specifically, we have applied Pearson correlation coefficients to describe those pairwise relations. Table 1 and Table 2 show the correlation values between criteria with statistical significance in parenthesis for the publication and the author impacts, respectively. For the publication impact in Table 1, the average author citation, average author h-index and average author i10-index are highly correlated and dependent to each other. The high significance values between duration and centrality; average author h-index and centrality; and average author i10-index and centrality do not provide strong evidence for their correlations. It should be also noted that citation and duration of a publication is positively correlated as said in the work [11]. Since they are positively correlated but citation needs to be maximized while duration needs to be minimized, they are in conflict.

For the author impact in Table 2, citation, h-index and i10-index are very correlated to each other. There is no strong evidence for duration and centrality; h-index and centrality; and i10-index and centrality. Similarly with the first table, the correlation between citation and duration of an author illustrates the conflict among them. In this work, we have chosen only three different objectives as the maximization of citation, the minimization of duration and the maximization of centrality to evaluate both publication and author impacts for better visualization.

B. Pareto-Fronts for Publication Impacts

The pareto-fronts for the publication impacts with 11 optimal publications in the top rank are given in Fig. 4. The citation objective (x-axis) is in the range of 0 to 8255, the duration objective (y-axis) is in the range of 0 to 14, and finally the centrality objective (z-axis) is in the range of 0 to 0.142. While the optimal publications are marked as red in the red surface, the other publications are marked as black. The optimal publications are not dominated by any other publications in the dataset with respect to the objectives considered. It is observed that although the publications are evenly distributed over the duration objective, they highly suffer from citation and centrality objectives. For instance, there are 593 out of 731 publications with less than 100 citations in our dataset.

The 30 most impactful publications for deep learning in autonomous vehicles are identified in Table 3 where each publication has name, NSGA-II rank, NSGA-II crowding distance, citation objective, duration duration objective and centrality objective from the citation graph. According to the pareto-

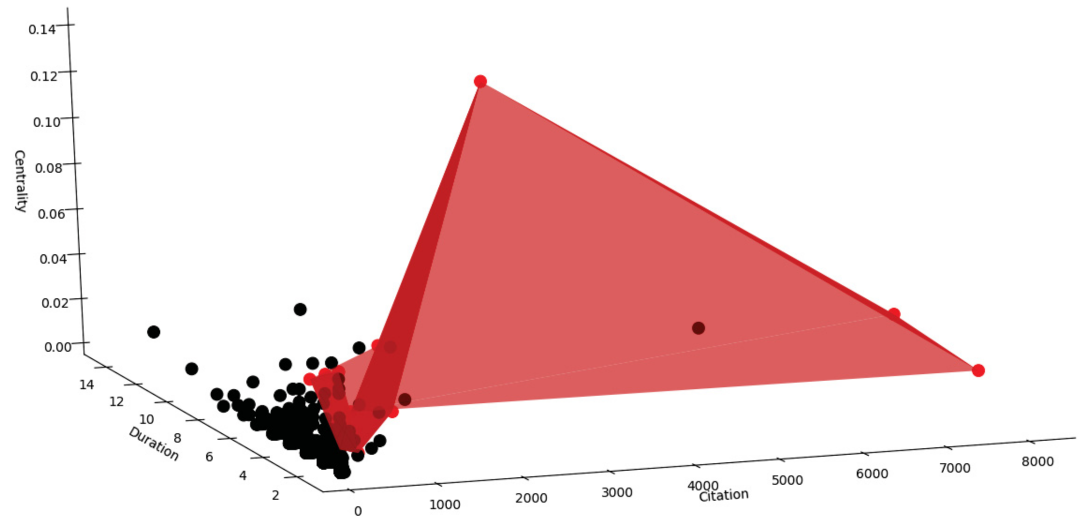

Fig. 4. The pareto-front for publication dataset

TABLE III. THE 30 MOST IMPACTFUL PUBLICATIONS FOR DEEP LEARNING IN AUTONOMOUS VEHICLES

	Name	Rank	C. distance	Citation	Duration	Centrality
1	End-to-end learning for self-driving cars [29]	0	INF	2487	5	0.142
2	Image-to-image translation with conditional adversarial networks [19]	0	INF	8255	4	0.011
3	Segnet: A deep convolutional encoder-decoder architecture for image segmentation [30]	0	0.366	7190	4	0.038
4	Voxelnet: End-to-end learning for point cloud based 3d object detection [31]	0	0.098	1008	3	0.015
5	A survey of deep learning techniques for autonomous driving [32]	0	0.085	130	1	0.025
6	Pointrcnn: 3d object proposal generation and detection from point cloud [33]	0	0.072	407	2	0.003
7	Multi-view 3d object detection network for autonomous driving [34]	0	0.042	1055	4	0.039
8	Deep learning approaches on pedestrian detection in hazy weather [35]	0	0.021	47	2	0.037
9	Deep learning methods in transportation domain: a review [36]	0	0.021	66	3	0.031
10	Argoverse: 3d tracking and forecasting with rich maps [37]	0	0.001	194	2	0.005
11	Learning to drive in a day [38]	0	0.001	166	2	0.010
12	An empirical evaluation of deep learning on highway driving [10]	1	0.709	558	6	0.048
13	Continuous control with deep reinforcement learning [39]	1	0.647	5295	6	0.029
14	Deepdriving: Learning affordance for direct perception in autonomous driving [40]	1	0.107	1236	6	0.030
15	CARLA: An open urban driving simulator [41]	1	0.028	1200	4	0.038
16	Multi-task learning using uncertainty to weigh losses for scene geometry and semantics [42]	1	0.019	858	3	0.003
17	Frustum pointnets for 3d object detection from rgb-d data [43]	1	0.012	854	3	0.015
18	Pointpillars: Fast encoders for object detection from point clouds [44]	1	0.001	400	2	0.002
19	A survey on 3d object detection methods for autonomous driving applications [45]	1	0.001	87	2	0.014
20	LIDAR-camera fusion for road detection using fully convolutional neural networks [46]	1	0.001	94	2	0.003
21	Traffic flow prediction with big data: a deep learning approach [47]	2	0.229	1968	7	0.002
22	End-to-end learning of driving models from large-scale video datasets [48]	2	0.229	515	4	0.002
23	Robust physical-world attacks on deep learning visual classification [49]	2	0.014	760	3	0.001
24	The synthia dataset: A large collection of synthetic images for semantic segmentation of urban scenes [50]	2	0.013	1026	5	0.010
25	3d object proposals for accurate object class detection [51]	2	0.012	522	6	0.014
26	Joint 3d proposal generation and object detection from view aggregation [52]	2	0.003	507	3	0.008
27	Deepxplore: Automated whitebox testing of deep learning systems [53]	2	0.003	575	4	0.001
28	Deeptest: Automated testing of deep-neural-network-driven autonomous cars [54]	2	0.002	562	3	0.004
29	Chauffeurnet: Learning to drive by imitating the best and synthesizing the worst [55]	2	0.001	235	3	0.014
30	Pseudo-lidar from visual depth estimation: Bridging the gap in 3d object detection for autonomous driving [56]	2	0.001	210	2	0.002

domination strategy, the publications are first ascendingly sorted by their ranks and then descendingly sorted by crowding distance in the same ranks. We believe that the identified publications can be efficiently used by researchers for education and technological advancements. As seen in the table, the best paper is ”End-to-end learning for self-driving cars” [29] published in 2016. It is observed that although some optimal publications have relatively low citations, their publication years are still very recent. For instance, the work, ”A survey of deep learning techniques for autonomous driving” [32], receives 130 citations in only a year.

From another perspective, some publications have very high citations, but they are relatively older. For instance, the work, ”Continuous control with deep reinforcement learning” [39], obtains 5295 citations in six years. The necessary performance increase can be also calculated for the publications to dominate the other publications in the future. The work ”Learning to drive in a day” [38] has potential to dominate the work ”Argoverse: 3d tracking and forecasting with rich maps” [37] in the future if it can receive at least 28 more citations.

C. Pareto-Fronts for Author Impacts

The pareto-fronts for the author impacts with 16 optimal publications are given in Fig. 5. The citation objective (x-axis) is in the range of 0 to 188204, the duration objective (y-axis) is in the range of 0 to 37, and finally the centrality objective (z-axis) is in the range of 0 to 0.065. The optimal publications are marked as red in the red surface and the rest of the publications are marked as black. Similar to the pareto-fronts for publication impacts, the research durations of the authors are evenly distributed, but there are 211 authors with less than 100 citations out of 1242 authors in our dataset. With that respect, the pareto-fronts of both publications and authors carry the same characteristics.

The 30 most impactful authors for deep learning in autonomous vehicles are identified in Table 4 where each author has name, affiliation, country, NSGA-II rank, NSGA-II crowding distance, citation objective, duration duration objective and centrality objective from the citation graph. Note that the authors are first ascendindly sorted by their ranks and then descendingly sorted by crowding distance in the same ranks. The most impactful author according to our proposed framework is Alex Kendall from University of Cambridge with 13946 citations within 6 years. The second and the third impactful authors are Yann LeCun from Facebook with 188204 citations within 29 years and Luc Van Gool from ETH Zurich with 141222 citations within 24 years. For the authors, the necessary performance increase can be calculated as well to dominate the other authors. We believe that the publications of the authors in the table have potential to change the domain of deep learning in autonomous vehicles in the future.

It is also interesting to analyse the author affiliations and countries in Table 4 where 16 authors out of 30 are from United States. This clearly demonstrates the major contribution of United States to the domain of deep learning in autonomous vehicles. The other noteworthy countries in the order of contributions are United Kingdom with four authors, Switzerland with two authors, Canada with two authors, Hong Kong with two authors, Germany with two authors, China with one author and finally South Korea with one author. The leading academical institution is University of California with four authors while the leading private corporation is Google with four authors.

VI. Conclusion

In this paper, we have proposed a multi-criteria evaluation framework to assess the publication and the author impacts in the domain of deep learning in autonomous vehicles. For the framework, different criteria have been considered including citations, durations and centrality in the citation graphs. The conflicts between criteria have been justified with respect to Pearson correlation where citation and duration are shown to be in conflict. For the experiments, two datasets have been separately constructed for the publications and the authors by collecting the relevant papers. Consequently, the pareto-fronts of the datasets are presented in three-dimensional objective space. Furthermore, the top 30 most impactful publications and authors are identified. The proposed methodology can also be applied to other research domains when the corresponding dataset is collected. In the future, we plan to construct a web-based dynamic multi-criteria evaluation framework.

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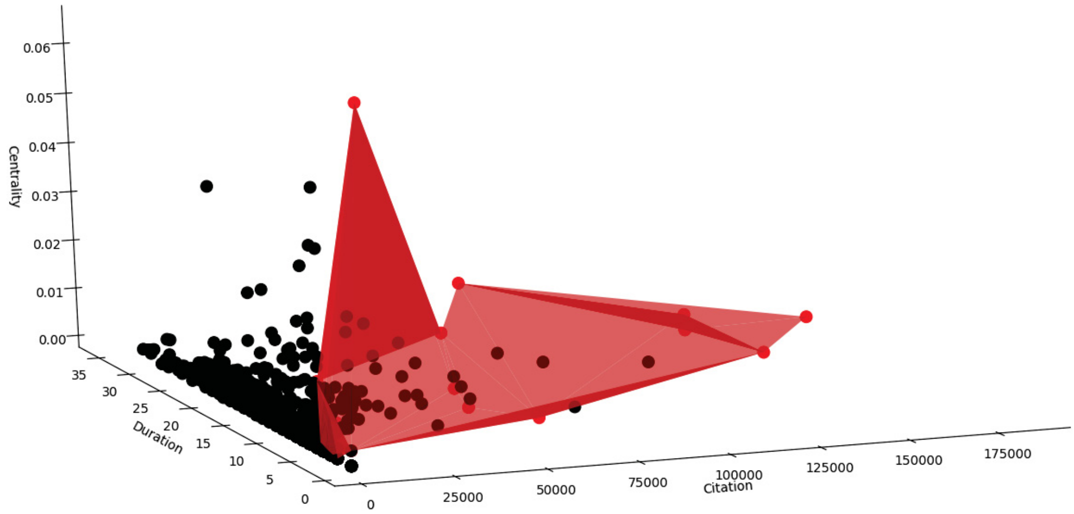

Fig. 5. The pareto-front for author dataset

TABLE IV. THE 30 MOST IMPACTFUL AUTHORS FOR DEEP LEARNING IN AUTONOMOUS VEHICLES

	Name	Affiliation	Country	Rank	C. distance	Citation	Duration	Centrality
1	Alex Kendall	University of Cambridge	United Kingdom	0	INF	13946	6	0.065
2	Yann LeCun	Facebook	United States	0	INF	188204	29	0.001
3	Luc Van Gool	ETH Zurich	Switzerland	0	0.290	141222	24	0.003
4	Alex Krizhevsky	Dessa	Canada	0	0.114	131491	9	0.009
5	Trevor Darrell	University of California	United States	0	0.094	138762	23	0.007
6	Dragomir Anguelov	Waymo	United States	0	0.063	53332	15	0.013
7	Timothy P. Lillicrap	Google DeepMind	United Kingdom	0	0.040	41338	7	0.008
8	Kyunghyun Cho	New York University	United States	0	0.036	66594	8	0.001
9	Wei Liu	University of North Carolina	United States	0	0.031	45169	7	0.004
10	Geoff Pleiss	Columbia University	United States	0	0.027	2636	5	0.001
11	Buyu Li	The Chinese University of Hong Kong	Hong Kong	0	0.027	667	3	0.001
12	Yurong You	Cornell University	United States	0	0.015	526	5	0.013
13	Amin Ullah	Sejong University	South Korea	0	0.015	821	4	0.006
14	Xiaogang Wang	The Chinese University of Hong Kong	Hong Kong	0	0.008	60241	16	0.022
15	Xiangyu Yue	University of California	United States	0	0.001	1006	5	0.002
16	Sourabh Vora	nuTonomy	United States	0	0.001	1055	5	0.001
17	Thomas Brox	University of Freiburg	Germany	1	0.033	60734	16	0.001
18	Yinhai Wang	University of Washington	United States	1	0.031	9582	18	0.022
19	Hao Su	University of California	United States	1	0.030	38816	11	0.004
20	Xiaodan Liang	Sun Yat-sen University	China	1	0.018	9043	7	0.010
21	Vijay Badrinarayanan	Wayve	United Kingdom	1	0.015	9649	10	0.012
22	Raquel Urtasun	University of Toronto	Canada	1	0.010	36926	16	0.006
23	Fisher Yu	ETH Zurich	Switzerland	1	0.003	14391	7	0.007
24	Alexey Dosovitskiy	Google Brain	Germany	1	0.003	17286	7	0.006
25	Pierre Sermanet	Google	United States	1	0.003	38138	10	0.003
26	Sergey Levine	University of California	United States	1	0.003	38612	8	0.001
27	Nicolas Heess	Google DeepMind	United Kingdom	1	0.002	17971	8	0.008
28	Phillip Isola	Massachusetts Institute of Technology	United States	1	0.002	24255	9	0.004
29	Jun-Yan Zhu	Carnegie Mellon University	United States	1	0.002	23901	7	0.004
30	Charles Ruizhongtai Qi	Waymo	United States	1	0.002	10323	6	0.004

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