SkateNet: A Data Set For Competitive Skating

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Abstract

The objectivity of scoring skateboarding tricks professionally has been questioned by viewers since the beginning of the sport. Like many other judge-scored sports, controversies are fairly common in professional skateboarding. No one has attempted to create a data set, or model to objectively rate skateboarding tricks. This project aimed to create a data set to help reduce controversy in further skate competitions. Once the data set was created, the validity of the clips in the data set was tested by classifying them using the MoViNet "a2" model[1]. The rating of individual tricks became somewhat impossible, because it is hard to separate which part of the trick accounts for how much of the total score in the trick combination. However, other aspects of skateboarding are more easily classified in binary categories such as stance, switch tricks, and successful attempts. A model was not able to be trained on these factors, but it is planned to be done in a future project.

1 Introduction

Before the addition of street skating to the Olympics, Street League Skating, or SLS, has been the premier street skating competition of the world. Skaters from around the world compete against each other with two 45-second runs and five best trick attempts. For the two runs, skaters normally attempt easier tricks that are more consistent. Runs in general are scored on complexity of tricks, variety of tricks, variety of obstacles, and how well each trick is done. For the best trick section, skaters complete five attempts of the best trick they can achieve. Each individual run and best trick attempt is scored on a 10 point scale. The top four scores from a skater are then totaled up, and skaters are ranked descending. Over the last 20 years, skaters have become increasingly skilled. Tricks previously attempted in the best trick section are now being performed in the middle of runs, where easier tricks are completed. The consistency of modern skaters would be unheard of if done in the past. Now, judges have started scoring skaters accordingly, with previously high rated tricks being worth less in the modern day.

A data set was created that can be used to train video recognition Artificial Intelligence to accurately classify and rate trick videos like a professional judge would in a street competition. There were three steps in producing this data set.

- First Supercrown, the championship of SLS, videos were downloaded off of SLS's YouTube channel[2].
- Next, best trick attempts were clipped from the downloaded YouTube videos.
- Finally, the accuracy of MoViNet's a2 model's predictions was tested on a random sample of the clips.

MoViNet's a2 model[1] is one of 3 video classification models produced by TensorFlow. The model is trained to recognize over 600 movements, including skateboarding. The a2 model was used to check if the data set was compatible with a popular modern video classification model.

2 Related Work

Skateboarding is one of the most popular sports in America. it had a "net worth of approximately 4.8 billion in 2010"[3] and it has only grown since then. "In a recent survey in the United States, skateboarding was found to be the third most popular sport among teenagers"[4] and with it's debut in the 2021 Olympics, the rise of skateboarding competition in the homes of families is here. Professional skateboarding is judged subjectively. "Generally, the assessment of skateboarding trick executions is completed abstractly dependent on the judges' understanding and experience"[3] and creating an objective rating for a specific trick can seem impossible. The inconsistency with "comprehensive feedback can make it hard to further improve the performance of athletes"[5]. At the professional level, an objective rating of skateboarding tricks could raise both the level of skateboarding and judging.

The rise of popularity of skateboarding also brings a new wave of learning skaters with it. Like any other physical activity, learning how to skateboard is time consuming. Many modern skaters look to online tutorials to learn new tricks. "Quite often, videos do not show the picture that its audience would like to visualize[4]. "Many tricks are best viewed from the back in order to show how it is done; however most videos are taken from the front where the result of the trick is nicely shown"[4]. Simple concepts in skateboarding, such as the Ollie, can be hard to conceptualize what movements are occurring to move the board in that way. "For spectators and beginners, a question which may come to their mind is "How on earth do they do that?"[4]. Learning a trick is the most dangerous part of skateboarding. "Given the growing popularity of this sport and its intrinsic risk factor, alternative ways to assist the development of this discipline should be pursued"[6]. With modern technology, there is no reason to continue with the outdated approach of watching recorded video. 3D modeling can be an excellent way to show all aspects of performing a trick to help beginning skaters learn quicker and safer. To both create an objective classifier to rate tricks and a 3D models for tricks, a large data set is vital to producing the best results.

The data set that will be creating can be used to train an AI to accurately judge tricks objectively. When similar projects have been done on other Olympic sports, they have used "13,310 videos"[7]. Data sets for skateboard trick classifiers have been created before, but many are not readily accessible for others to train their models on. Every project has had to create their own data set to train their model on, resulting in much smaller data sets. In a recent project, Hanxio Chen created a data set of "750 videos"[8].

The data set "plays a critical role in machine learning"[9]. In a similar problem to trick classification, classifying code smells has been looked at extensively. With statistical and learning based approaches, "automatic smell detection requires a large data set with annotated samples for each smell"[10]. "The performance of a code smell detection tool is vastly affected by the data set that it was trained on"[10]. With classification of any kind, the size of the data set is one of the most important properties. Classifying code smells and skateboard tricks may seem like two completely unrelated fields, but the general essence between the two is the same. Similar to classifying code smells, a large data set is paramount to creating a good classifier for skateboarding tricks. With most projects not releasing their data sets and every project having to start from scratch, it is very hard to achieve the level of accuracy that other models have with larger data sets.

Data sets should be publicly available so that other computer scientists and academics can build off of the work of others to create better models. With a small data set on a complex topic, researches may be tempted to fine tune models to fit what they have. There are many nuances to how humans do things naturally and accommodating for all of them in a model is almost impossible. "If that's so, we should stop acting as if our goal is to author extremely elegant theories, and instead embrace complexity and make use of the best ally we have: the unreasonable effectiveness of data"[11].

A large amount of data can help train an AI to make up for the mysteries of natural human things. Subjects, like speaking, have vast corpuses devoted to just encoding engrams to train AI. There is no reason why other less practical topics should get any different treatment. Innovation is often found when people are attempting experiments considered "wild" by many, but that creativity is what can lead to some of the greatest advancements. By having smaller project data sets kept private, we are limiting the progress of AI as a whole. "The development of trustworthy AI heavily depends on data"[12] and by limiting access to that data, we limit our progress in AI.

Creating a data sets for machine learning and 3D model creation are important to the advancement of skateboarding as a whole. Making data sets publicly available are important to advancing AI. These topics may seem distant, but embracing less practical interests can help to promote innovation in the field as a whole. By keeping data sets private, we are halting advancements.

3 Data

In order to create the data set, inspiration was taken from voglobinsky's[13] skateboarding-tricks database and skatesense.com's[14] competition and skater databases. Videos were collected from SLS's[2] YouTube channel. Clips were taken from YouTube using the pytube library. Once the entire video is downloaded, individual clips are created using Quicktime's video trimming. Video clips were named based off of the trick that was completed, the stance of the skater, and the score given. A random sample of the videos was tested on a model for accurate classification if a video contained skateboarding. All of the information from the clips will be stored in a DataFrame[15] for ease of access. All of the clips and the DataFrame are available at [16].

Each entry in the DataFrame contains the name of the video, rating, stance of the skater, all of the tricks completed, the first trick, second trick, third trick, the location of the event, and the year completed. These are stored in the columns video, rating, stance, tricks, trick1, trick2, trick3, location, and year respectively. The columns trick2 and trick3 can have N/A values because some attempts only consist of one or two tricks.

Figure 1: Gustavo Ribiero doing a bigger flip into a backside boardslide

Video	Rating	Stance	Tricks Completed	First Trick	Second Trick	Third Trick	Location	Year
G Bigger Flip + BS Boardslide 9,1.mp4	9.1	G	Bigger Flip + BS Boardslide	Bigger Flip	BS Boardslide	N/A	Jacksonville	2021

The data set contains slow-mo clips for all of the successful attempts. Clips are stored in the highest resolution of the video generally, usually 1920 x 1080p. The process of collecting the data is extremely tedious and impossible to automate. Also, there are no attempts on trick combinations scoring between 0 and 7. This makes the data extremely bimodal, which is not beneficial for comparative scoring to non-professional trick combinations. Only 3 competitions were used in the creation of this data set, so all of the tricks for each year were attempted on the same day in the same park.

	video	rating	stance	tricks	trick1	trick2	trick3	location	year
0	G BS Noseblunt Slide 7,5.mp4	7.5	G	BS Noseblunt Slide	BS Noseblunt Slide	N/A	N/A	Jacksonville	2021
1	R Switch BS Noseblunt slide 9,0 slowmo.mp4	9.0	R	Switch BS Noseblunt slide	Switch BS Noseblunt slide	N/A	N/A	Jacksonville	2021
2	G Bigger Flip + BS Boardslide 9,1 slowmo.mp4	9.1	G	Bigger Flip + BS Boardslide	Bigger Flip	BS Boardslide	N/A	Jacksonville	2021
3	G FS 270 + BS Lipslide 0,0.mp4	0.0	G	FS 270 + BS Lipslide	FS 270	BS Lipslide	N/A	Jacksonville	2021
4	R Kickflip + BS Lipslide 0,0.mp4	0.0	R	Kickflip + BS Lipslide	Kickflip	BS Lipslide	N/A	Jacksonville	2021
5	G Full Cab + BS Noseblunt slide 9,0.mp4	9.0	G	Full Cab + BS Noseblunt slide	Full Cab	BS Noseblunt slide	N/A	Jacksonville	2021
6	G Switch FS Flip + Switch FS Tailslide 9,0 sl...	9.0	G	Switch FS Flip + Switch FS Tailslide	Switch FS Flip	Switch FS Tailslide	N/A	Jacksonville	2021
7	G Bigger Flip + BS Boardslide 9,1.mp4	9.1	G	Bigger Flip + BS Boardslide	Bigger Flip	BS Boardslide	N/A	Jacksonville	2021
8	G Kickflip + BS Lipslide 0,0.mp4	0.0	G	Kickflip + BS Lipslide	Kickflip	BS Lipslide	N/A	Jacksonville	2021
9	G BS Bigspin + BS Tailslide 0,0.mp4	0.0	G	BS Bigspin + BS Tailslide	BS Bigspin	BS Tailslide	N/A	Jacksonville	2021
10	G Switch FS Flip + Switch FS Tailslide 9,0.mp4	9.0	G	Switch FS Flip + Switch FS Tailslide	Switch FS Flip	Switch FS Tailslide	N/A	Jacksonville	2021
11	G Switch Flip + Switch BS Nosegrind 0,0.mp4	0.0	G	Switch Flip + Switch BS Nosegrind	Switch Flip	Switch BS Nosegrind	N/A	Jacksonville	2021
12	G BS Noseblunt Slide 7,5 slowmo.mp4	7.5	G	BS Noseblunt Slide	BS Noseblunt Slide	N/A	N/A	Jacksonville	2021
13	G Bigger Flip + FS Boardslide 0,0.mp4	0.0	G	Bigger Flip + FS Boardslide	Bigger Flip	FS Boardslide	N/A	Jacksonville	2021
14	G Full Cab + BS Noseblunt Slide 0,0.mp4	0.0	G	Full Cab + BS Noseblunt Slide	Full Cab	BS Noseblunt Slide	N/A	Jacksonville	2021
15	R Switch BS Noseblunt slide 9,0.mp4	9.0	R	Switch BS Noseblunt slide	Switch BS Noseblunt slide	N/A	N/A	Jacksonville	2021
0	G Switch Heel + FS Tailslide 9,40 slowmo.mp4	9.4	G	Switch Heel + FS Tailslide	Switch Heel	FS Tailslide	N/A	Tokyo	2023

Figure 2: First entries in the DataFrame

4 Methods

The championships from Tokyo 2023, Rio 2022, Jacksonville 2021 were the three videos used to create the clips. They were downloaded from YouTube using the pytube[17] library. Mac's quick-time video trimmer was used to create the clips. They are labeled based off the stance of the skater, the trick name, and then the score given. A goofy stance skater doing a backside bigger flip into a backside boardslide that received a 9.1 rating would be saved as "G Bigger Flip + BS Boardslide 9,1.mp4". All of the information was stored inside of a DataFrame[15] for ease of access. The model was trained using tensor flow's MoViNet's video classification model[1]. The model is fed the clips as a series of frames stored in tensors. All of the color values are normalized to be between 0 and 1 instead of the normal 0 and 255. The clips' resolution are reduced to 224 x 224 when they are given to the model. This is because the version of the MoViNet model used, a2, does not work optimally with higher resolution videos than 224 x 224. The model outputs the top five "labels", one of the 600+ movements the model was trained to recognize, and it's confidence in that movement. A random sample of 30 was fed to the model. Each time a clip was processed, the labels were put into a dictionary where the keys were the label, and the value was the sum of all the confidence values recieved for that label so far. The average of each key's confidence value was then put in a DataFrame. All of the video clips, DataFrames, and models are available at [16].

5 Results

To test the validity of the data set, MoViNet's a2 model[1] was used to classify the videos into categories of activities. On a random sample of 30 videos, the model classified them as skateboarding with 85.7% confidence. This may seem like a low percentage, but the other 14.6% is split among 24 other movements. The top five most confident results after skateboarding were bobsledding, long jump, ski jumping, triple jump, and face planting.

Skateboarding	Bobsledding	Long Jump	Ski Jumping	Triple Jump	Face Planting
85.7%	1.9%	1.8%	1.6%	1.2%	1.2%

Long jump, triple jump, and ski jumping all have large crowds watching an athlete fly through the air. This is very similar to competition skating. Most of the video clips have the crowd behind the skater in the air, so the 1-2% confidence rating in long jump, triple jump, and ski jumping makes sense. Face planting's 1.2% confidence rating can be explained by the failed attempts in the data set. Many failed attempts end with skaters with both hands above their head facing the ground3.

The Bobsledding confidence rating of 1.9% and its position in second place is much harder to resolve. This can also possibly be explained with failed attempts, as many times skaters will slide on their backside after failing an attempt. When sliding, their momentum often carries their top half backwards, resulting in a leaned back slide4.

Figure 3: Tommy Fynn attempting a backside flip 5-0

Figure 4: Kelvin Hoefler attempting full cab backside tailslide

Training a model to understand the intricacies of trick rating at a professional level has proven too complicated at this point. The bimodal distribution of scoring and the lack of individuality of trick clips makes it hard to score tricks. There are no tricks within the three competitions used in the data set that were between 0 and 7, as seen in 6. Also, rarely are individual tricks attempted. An individual trick attempt would result in a low score. A combination of tricks is required to get an average score. This can make it hard to an untrained person to discern the number of tricks in the attempt, let alone the types of tricks themselves. For example, here is an image5 of Yuto Horigome attempting a nollie frontside 270 into a switch backside tailslide. At the time of this image, he is transferring from the frontside 270 into the tailslide. It is extremely ambiguous as to where the frontside ends and the tailslide begins.

Figure 5: Yuto Horigome attempting a nollie frontside 270 into a switch backside tailslide

This makes it nearly impossible to train a model for individual trick scoring, but makes it easy to assess attempt completion or failing. The distribution of trick stances, or which foot the skater has in front, is very nice 6 with an almost equal distribution between goofy and regular. This is very beneficial for training a model to recognize stance or switch tricks. All in all, training a model for individual trick scoring is currently extremely hard. Trick combination scoring may be possible in the future with a larger data set. Things like stance, determining if a trick is switch, and successful attempts are easy to classify because they have a binary nature.

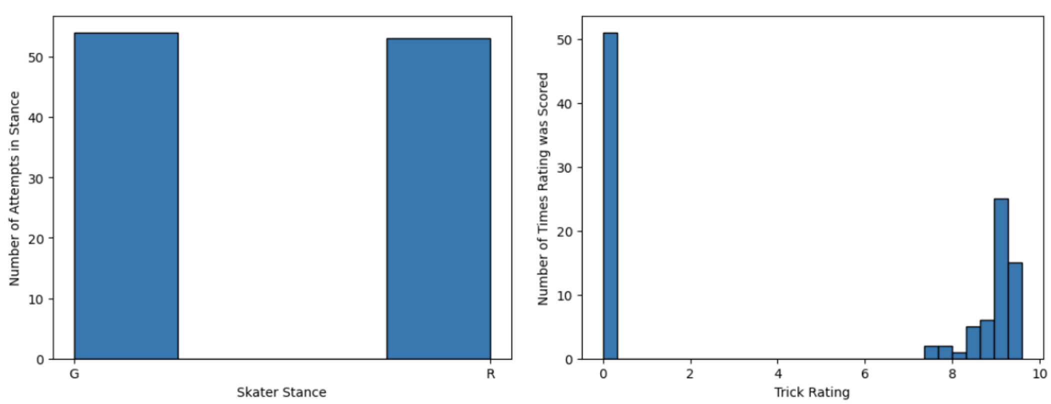

Figure 6: Stance and Trick Distribution

6 Future Work

The biggest limitation with this project is the lack of contextual skills the model has in comparison to a person. A majority of the tricks completed in a skating competition consist of two tricks. The first one is done in the air, while the second one is done in a grid trick. This can be done on a ledge or a handrail. The rating of a trick is based on these tricks in combination. There is no way to split up the scoring between the two tricks, so it makes it very hard to rate tricks individually. Also, skaters generally only attempt winning tricks, so there is no data for attempts between 0 and 7. The data is extremely bimodal, so that makes it hard to assess tricks with ratings. With a larger data set, models could be trained on combinations of tricks and rate them, but this is not helpful for individual trick classification. Instead of assessing tricks on a 0-10 scale and not using anything between 0 and 7, the scale could be adjusted to be from the lowest scored trick to 10. That way the data would not be bimodal. This would allow there to be an actual distribution, since the zeros from missed attempts would not be separated from the made attempts.

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