Towards Sustainable Conferences: An Analysis of SIGPLAN Registration Data

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In 2017, ACM's Special Interest Group on Programming Languages (SIGPLAN) formed an ad-hoc committee to study issues related to climate change—in particular, how SIGPLAN might contribute to the 40% reduction in carbon emissions by 2030 that the IPCC tells us is needed to maintain warming under 1.5°C [Masson-Delmotte et al. 2018]. One important part of this effort has been to gather data pertaining to SIGPLAN conferences so to gain a better understanding of their present emissions. This paper explains the data we gathered and presents some preliminary analysis of this data. Our main finding is that there is an inherent conflict between SIGPLAN's goal of geographic inclusiveness and the goal of reducing carbon emissions, and that, going forward, innovative approaches for how to organize conferences that are both inclusive and carbon efficient will be needed.

We believe that other research communities can benefit from performing a similar introspection and drawing their own conclusions from results. To this end, we also describe the open-source Python scripts we developed to conduct our analysis.

Additional Key Words and Phrases: Climate change, conferences, carbon footprint, air travel, SIGPLAN, ACM

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1 INTRODUCTION

Given the existential threat of global warming, it is incumbent on every individual and organization to evaluate the carbon emissions footprint generated by their activities and consider ways to reduce them. For many academic researchers, this footprint will overwhelmingly come from air travel, especially to international conferences.

This observation raises a number of questions about how to organize our activities so as to maximize progress while minimizing emissions. Should SIGPLAN conference locations be chosen to minimize their carbon impact? If so, how? Should we move toward co-locating conferences? Or, on the contrary, should some conferences be split into regional meetings or held simultaneously at two sites on different continents? More drastically, do we need to hold some conferences entirely virtually?

To ground discussions about the decisions and compromises that the scientific community may collectively wish to undertake, we consider three main classes of data whose analysis may guide our decisions.

- The estimated emissions of past conferences.
- The geographical distribution of participants to conferences.
- The overlap in participation between various conferences.

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We outline the results of a preliminary analysis effort on the past several years of registration data for four of the main SIGPLAN conferences. We hope this effort can server as a basis both for debates about concrete measures as well as for larger scale and farther reaching studies.

After briefly describing our dataset in Section 2, we present an estimate of the SIGPLAN conferences' footprint in Section 3. Section 4 is the core of our analysis: we derive several statistics about the geographical distribution of the participants and their habits of cross participation, across time and across conferences, arguing that these data are correlated to the footprint. We then present in Section 5 a speculative experiment aiming to estimate the ideal locations for the conferences in order to minimize the footprint. Finally, we advertise for the use of the open source tool we developed to conduct our analyses in Section 6, hoping that other communities might piggyback on our effort to conduct similar studies.

2 DATASET

Our dataset consists of 10 years worth of attendance to the four major SIGPLAN conference series—POPL, PLDI, ICFP, and SPLASH—from the beginning of 2009 until the end of 2018. Data for some of the conferences in the earlier years are missing. In total, we have data for 33 conferences, corresponding to 8,758 unique participants and 16,374 trips. For each participant, we know all the conferences (s)he attended, and from which city (s)he departed to attend the conferences. The names of participants are replaced in the dataset by unique hashes, obscuring each individual's identity while allowing them to be identified across years and across the conferences they attended.

3 ESTIMATING THE FOOTPRINT OF CONFERENCES

Carbon footprint is the essential metric that we seek to reduce. Accordingly, it is also the starting point of our analysis. We introduce in this section the methodology we used and tool we built to conduct all of our analyses, and we describe the first results from our dataset.

3.1 Methodology for Evaluating Carbon Cost

We conduct all our analyses through a Python 3 script, publicly available at https://github.com/YaZko/acm-climate. We describe its behavior and give a brief overview of its use in Section 6.

We make the following assumptions:

- we assume that participant travel accounts for the entire carbon footprint of a conference;
- we assume that *all* participants travel by plane, in economy class;
- we assume that the airports in the conference city and in each participant's home city are close enough to the actual end points of their travel for their locations to be assimilated;
- we assume that all flights are direct;
- we assume that the geodesic distance is the one taken by planes.

Estimating the errors introduced by these assumptions and refining the analysis to make more realistic assumptions would obviously be very valuable! For this first effort, we are mainly aiming to get a *relative* evaluation of different potential strategies for reducing footprints; for this purpose, we believe these assumptions are good enough.

The distance traveled by each participant is converted to an amount of emissions expressed in kg_{CO_2e}. To do this conversion, we use a standard model introduced as part of the `DEFRA 16` report on Greenhouse gas [1] [2] conducted by the British Government.

The model distinguishes three classes of flight, depending on their length: short, medium, and long haul. Each category is associated with a linear coefficient relating the distance of travel to the amount of kg_{CO_2e}emitted.

[1] https://www.gov.uk/government/publications/greenhouse-gas-reporting-conversion-factors-2016
[2] https://co2calculator.acm.org/methodology.pdf

A second linear coefficient, identical for all flights, is the so-called *radiative forcing index*; this is used to account for the difference in radiative forcing between the same emissions at ground level compared to high in the atmosphere. We use the value 1.891 for this coefficient, as suggested by R. Sausen et al. [Sausen et al. 2005]

We thus obtain the following piecewise-linear model of emissions for a flight covering d kms:

$$\text{kg}\,(\text{CO}_2\text{e})\,\text{per participant} = \begin{cases} 1.891 * 0.14735 * d & \text{if } d < 785 \\ 1.891 * 0.08728 * d & \text{if } 785 \leq d < 3700 \\ 1.891 * 0.077610 * d & \text{if } 3700 \leq d \end{cases}$$

3.2 Conference Footprints

We now turn to the estimation of the footprint of our dataset. Table 1 depicts the total and average carbon cost per participant of all conferences analyzed. This cost is estimated in terms of t_{CO_2e} (metric tons of CO_2-equivalent) of emissions. The main data of interest is arguably the last column depicting the average cost per participant.

The lowest average per-participant cost of our dataset is PLDI'18 at $0.9t_{CO_2e}$, while the highest one is ICFP'16 at $1.93t_{CO_2e}$.

Observation 1. *The average per participant carbon footprint of conferences due to air travel varies from one to another by up to a factor of 2.*

4 DATA ANALYSIS: COMMUNITY

The greenhouse gas emissions from a given event is in direct proportion to the average distance traveled by the participants of this event. To understand emissions, we must therefore estimate the nature of the communities that attend each conference.

The aggregated information we describe below falls into two main categories: first, the demographic distribution of the participants to the conferences conditioned by various factors, and second, the participation habits of the community through recurring participation to a given conference and the overlap in participation between different conferences.

4.1 Demographics: Where Did Participants Come From?

Figure 2[3] and Table 3 show where all participants came from. For each conference, we depict the distribution of attendance per continent. Table 3 shows the portion of attendants originating from the same continent as the one the event took place in. To a first approximation, maximizing this last metric, i.e. hosting conferences in the continent containing the majority of its community, is a good thing.

Taken as a whole, these conferences attracted 50% participants from North America, 36% from Europe, 11% from Asia, 2% from Oceania, 1% from South America, and less than 0.2% from Africa. The data also displays some degree of geographical affinity for the various conferences. Notably, PLDI and SPLASH appear to be quite North-America-centric, while ICFP's core community seems to have a strong anchor in Europe as well.

This overall picture, however, hides some interesting facts pertaining to the relationship between the conferences' locations and the origin of the participants. Indeed, aggregating the attendance per conference intrinsically rests upon the assumption of a uniform community attending each instance of the conference every year. Table 5 and Figure 5 show a more detailed breakdown of the origin of participants for each conference, showing also the geographic region where the conferences were held.

These charts make it clear that the location of the conferences had a substantial effect on attracting people from the same geographic areas. That effect is quite visible for ICFP and POPL, with noticeable ups and downs of the colored bars between North American and European participants when the conferences were located in

[3]The graphical representations in this preliminary draft are based on a slightly different version of our dataset than the one used by our tool. There may be some minor discrepancies between these representations and the raw tables presented.

Event	Location	# Participants	Total cost	Average cost
ICFP 10	Baltimore	336	399.44	1.19
ICFP 11	Tokyo	336	518.27	1.54
ICFP 12	Copenhagen	481	422.34	0.88
ICFP 13	Boston	505	512.06	1.01
ICFP 14	Gothenburg	483	426.35	0.88
ICFP 15	Vancouver	439	636.14	1.45
ICFP 16	Nara	528	1019.65	1.93
ICFP 17	Oxford	592	610.05	1.03
ICFP 18	St. Louis	487	572.49	1.18
POPL 9	Savannah	331	488.19	1.47
POPL 11	Austin	403	595.97	1.48
POPL 12	Philadelphia	536	586.16	1.09
POPL 13	Rome	540	658.2	1.22
POPL 14	San Diego	533	905.64	1.7
POPL 15	Mumbai	463	748.24	1.62
POPL 16	St. Petersburg	488	695.45	1.43
POPL 17	Paris	719	671.79	0.93
POPL 18	Los Angeles	576	932.93	1.62
PLDI 9	Dublin	255	381.48	1.5
PLDI 13	Seattle	467	595.13	1.27
PLDI 14	Edinburgh	427	545.71	1.28
PLDI 15	Portland	465	599.0	1.29
PLDI 16	Santa Barbara	438	575.25	1.31
PLDI 17	Barcelona	495	784.67	1.59
PLDI 18	Philadelphia	468	421.32	0.9
SPLASH 9	Reno	709	1125.85	1.59
SPLASH 10	Sparks	566	821.57	1.45
SPLASH 12	Tucson	434	665.03	1.53
SPLASH 13	Indianapolis	606	668.87	1.1
SPLASH 14	Portland	491	625.91	1.27
SPLASH 15	Pittsburgh	611	777.82	1.27
SPLASH 16	Amsterdam	584	595.63	1.02
SPLASH 17	Vancouver	582	864.69	1.49

Table 1. For each event: location, number of participants and carbon cost, total and average per participant, in t_{CO_2e},

North America and Europe, respectively. Most strikingly, Asian participation during POPL '15, ICFP '11 and ICFP '16, events that took place on the Asian continent, is significantly higher than usual: there appears to be a strong locality phenomenon. Crossing this data with Table 1, one can also notice that the only time SPLASH took place in Europe turned out to be the least carbon-intensive edition, challenging our previous observation that the conference appears to be mostly North-America-centric.

Table 6 attempts to measure this locality effect. The table depicts, all conferences being considered at once, the geographical distribution of attendance conditioned by the geographical location of the event. The Asian phenomenon previously hinted at is here extremely apparent: while overall on average, 10.9% of the participants

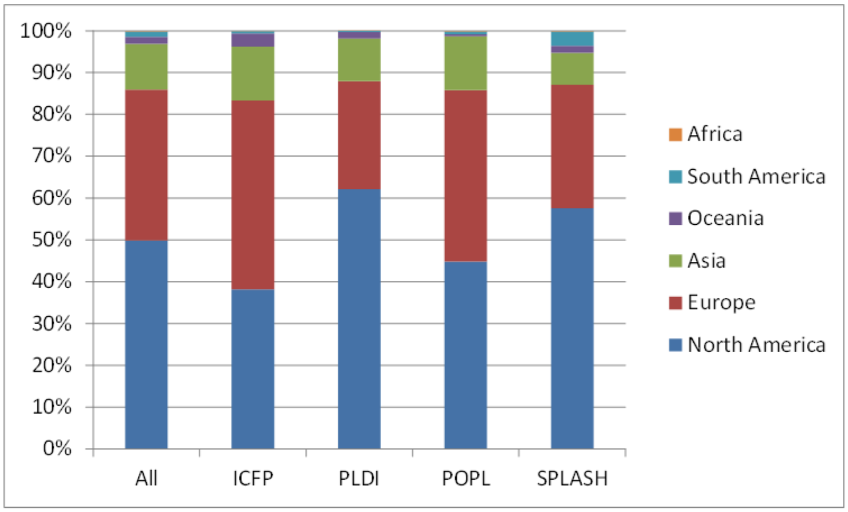


Fig. 2. Overall origin of participants per conference.

Conference	EU	NA	AS	SA	AF	OC	Local
ICFP	45.09	38.19	12.9	0.62	0.1	3.1	59.18
POPL	41.01	44.82	12.77	0.7	0.17	0.52	56.98
PLDI	25.84	62.16	10.08	0.36	0.03	1.53	60.13
SPLASH	29.61	57.47	7.64	3.43	0.17	1.68	61.75
Any	36.07	49.86	10.87	1.38	0.13	1.69	59.46

Table 3. For each kind of conference, distribution of participants per continent of origin

come from Asia, this number is roughly multiplied by a factor 4 when the event takes place in Asia – without any significant drop in total volume of attendance that could indirectly bump the percentage. But interestingly, this phenomenon also exists in the case of Europe (+22.29% deviation to the average) and North America (+12.15% deviation to the average). Despite their name, international conferences appear to exhibit a fairly strong local component.

Overall, this data shows that the goal of geographic inclusion was, indeed, accomplished by organizing the conferences in diverse geographic areas of the world. It also places Figure 5 into a broader context: a naive interpretation of that chart might lead us to conclude that North America and Europe are where most of this community is, but it is not that simple. Because of the regional effect on participation, the distribution of participants also reflects the fact that most of these conferences were held in North America and Europe (30), only a few were held in Asia (3), and none was held in South America, Oceania, or Africa.

The situation may be summed up in two elementary observations:

Observation 2. *The vast majority of participants are split between North America and Europe, Asia to a much lesser degree. SPLASH and PLDI are strongly anchored in North America, ICFP and POPL fairly equally split between North America and Europe.*

This distribution, however, is *strongly* dependent on the location of the event.

Conference	Year	Continent	EU	NA	AS	SA	AF	OC	Local
ICFP	10	NA	34.82	55.95	8.33	0.0	0.0	0.89	55.95
ICFP	11	AS	33.04	17.86	46.43	0.0	0.0	2.68	46.43
ICFP	12	EU	70.06	22.45	6.03	0.21	0.0	1.25	70.06
ICFP	13	NA	31.09	62.18	3.56	0.99	0.0	2.18	62.18
ICFP	14	EU	72.26	19.25	4.55	0.62	0.0	3.31	72.26
ICFP	15	NA	28.93	58.54	5.01	1.59	0.46	5.47	58.54
ICFP	16	AS	32.01	24.43	35.98	0.76	0.19	6.63	35.98
ICFP	17	EU	64.19	24.16	7.26	0.17	0.17	4.05	64.19
ICFP	18	NA	28.95	63.04	6.57	1.03	0.0	0.41	63.04
POPL	9	NA	39.88	49.24	9.37	0.6	0.0	0.91	49.24
POPL	11	NA	35.24	56.08	7.94	0.0	0.0	0.74	56.08
POPL	12	NA	29.48	61.01	8.4	0.19	0.19	0.75	61.01
POPL	13	EU	58.89	29.44	11.3	0.19	0.0	0.19	58.89
POPL	14	NA	36.59	54.22	6.94	1.31	0.19	0.75	54.22
POPL	15	AS	29.37	21.6	48.6	0.0	0.22	0.22	48.6
POPL	16	NA	33.4	57.79	7.79	0.61	0.2	0.2	57.79
POPL	17	EU	63.56	25.45	8.9	1.25	0.42	0.42	63.56
POPL	18	NA	31.42	56.94	9.2	1.56	0.17	0.69	56.94
PLDI	9	EU	29.8	59.61	8.63	0.39	0.39	1.18	29.8
PLDI	13	NA	18.2	69.38	10.28	0.21	0.0	1.93	69.38
PLDI	14	EU	42.86	44.26	10.54	0.7	0.0	1.64	42.86
PLDI	15	NA	20.65	70.75	7.31	0.0	0.0	1.29	70.75
PLDI	16	NA	13.93	73.29	11.87	0.0	0.0	0.91	73.29
PLDI	17	EU	43.23	38.99	14.14	1.01	0.0	2.63	43.23
PLDI	18	NA	13.68	78.21	7.05	0.21	0.0	0.85	78.21
SPLASH	9	NA	25.39	61.35	8.18	3.53	0.28	1.27	61.35
SPLASH	10	NA	23.32	62.9	8.83	2.83	0.18	1.94	62.9
SPLASH	12	NA	22.35	62.21	11.52	2.3	0.23	1.38	62.21
SPLASH	13	NA	24.75	65.02	4.79	3.96	0.17	1.32	65.02
SPLASH	14	NA	19.96	68.84	4.68	4.28	0.2	2.04	68.84
SPLASH	15	NA	30.28	56.14	7.2	4.09	0.0	2.29	56.14
SPLASH	16	EU	60.96	27.4	8.22	2.05	0.34	1.03	60.96
SPLASH	17	NA	27.32	58.08	8.25	4.12	0.0	2.23	58.08

Table 4. For each event, continent in which it took place and distribution of each continent by origin of participants. The final column indicates the portion of participants that traveled from the same continent the conference took place in.

Observation 3. *There is a major "locality" effect: it is both true that locality attract new participants, and distance repels some participants.*

4.2 How Often Did Participants Attend These Conferences?

Section 4.1, through the study of the demographic distribution of attendance, has suggested the existence of local communities that only partake in conferences when they take place close to their place of residency. One can conversely look for groups of regular attendees, that participate to a given regardless of the location it is held in.

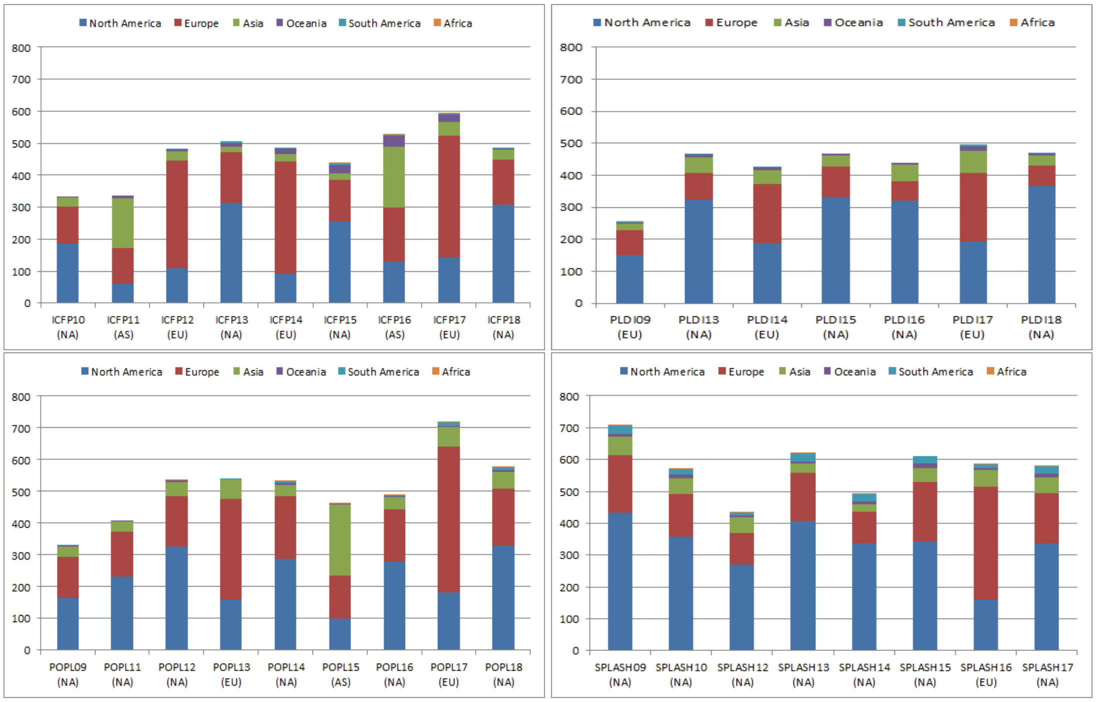


Fig. 5. Origin of participants for each conference, detail.

Location	EU	NA	AS	SA	AF	OC	Local
EU	58.35	30.16	8.83	0.79	0.15	1.73	58.35
NA	26.93	62.03	7.69	1.78	0.11	1.46	62.03
AS	31.35	21.78	43.03	0.3	0.15	3.39	43.03
Any	36.07	49.86	10.87	1.38	0.13	1.69	59.46

Table 6. Geographical distribution of participation conditioned by the location of the event

Figure 7 shows how often the same participants attended multiple conferences. At the extremes, 6,009 people (69%) attended only 1 conference, and 4 people attended 20 or more conferences. Participation is dominated by single-conference participants, perhaps reflecting a large and transient student population. The pattern is similar for each conference series, shown in Figure 8.

4.3 What Was the Participation Overlap Between These Conferences?

We now take a closer look at the habits of these recurring participants.

A first natural question is to ponder whether there is a significant overlap in participation between conferences. Table 9 depicts, for each pairing of the four conferences, the percentage of overlap. This measure is strikingly low for most conferences.

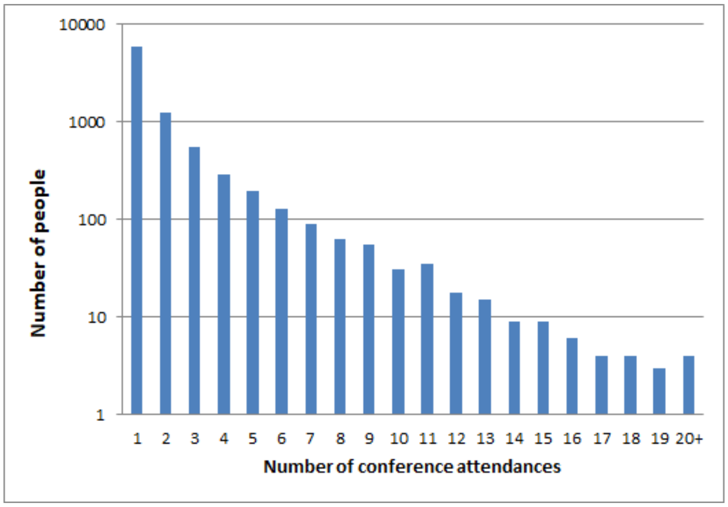


Fig. 7. Histogram of attendance.

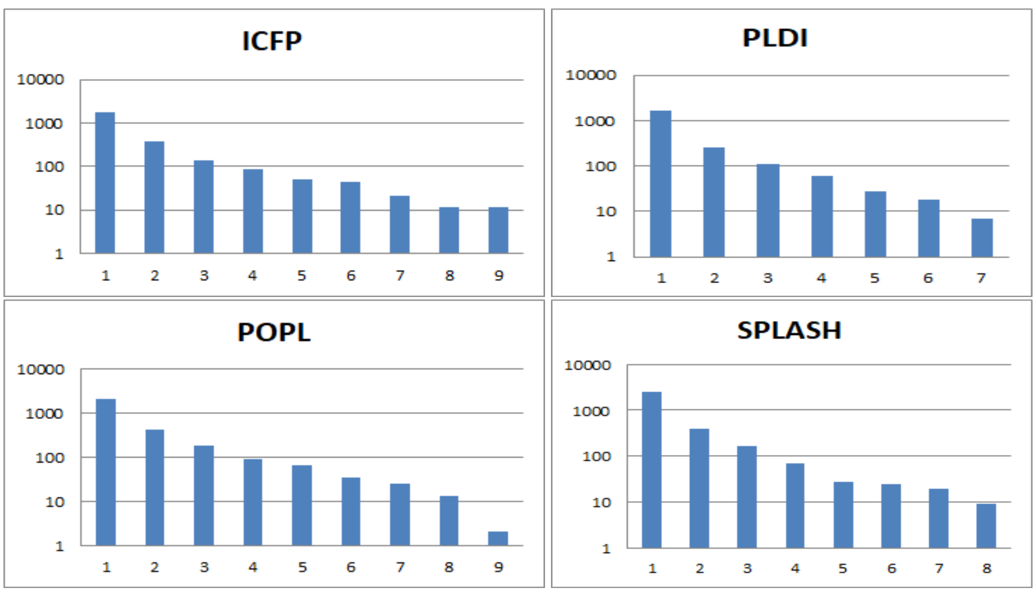


Fig. 8. Histogram of attendance for each conference series.

Observation 4. *Cross-conference overlap is low: the tightest pairing sees slightly over 10% of common attendance for a given year. Extending the overlap among any two years, the tightest pairing still sees less than a quarter of unique participants having participated at least once in both conferences.*

Conversely, one can estimate the overlap for a given conference over time: for a given conference at a time, and for any pair of years, compute the percentage of attendees that participated in both events. This new

Year	Overlap
11	10.87
12	14.95
13	16.27
14	11.81
15	5.99
16	11.02
17	13.58
18	13.94
Any	22.82

(a) POPL and ICFP

Year	Overlap
9	7.86
13	10.72
14	14.17
15	6.68
16	12.1
17	10.05
18	13.04
Any	24.15

(b) POPL and PLDI

Year	Overlap
9	3.27
12	7.22
13	5.41
14	8.01
15	2.79
16	5.97
17	5.84
Any	13.16

(c) POPL and SPLASH

Year	Overlap
13	4.94
14	4.4
15	4.65
16	2.9
17	6.26
18	7.33
Any	11.24

(d) ICFP and PLDI

Year	Overlap
10	2.66
12	1.97
13	2.52
14	2.46
15	3.81
16	3.42
17	3.41
Any	8.06

(e) ICFP and SPLASH

Year	Overlap
9	4.78
13	11.37
14	10.02
15	13.01
16	6.85
17	13.74
Any	18.94

(f) PLDI and SPLASH

Table 9. For every year, overlap in attendance between the events of two different conferences. The "Any" row depicts the percentage of unique participants that went at least once to both conferences over the available years of data.

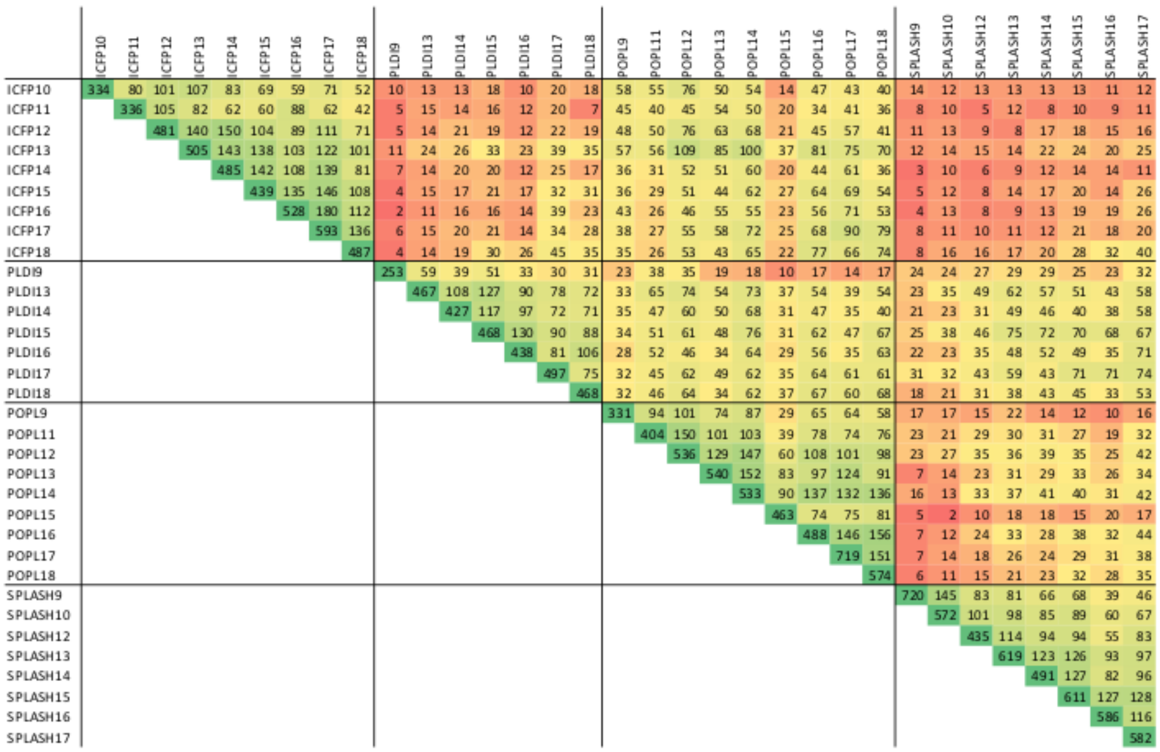
information, as well as the essential of Table 9, is synthesized graphically on Figure 10. With this bird-eye view of the permanence vs. transience of the participants over time in SIGPLAN conferences, we can make a second observation, temporal this time:

Observation 5. *Temporal overlap is moderate: roughly a quarter of attendees at a given conference were also present the year before at the same conference.*

In principle, it is desirable to have a balance between repeat participants and newcomers. Communities that don't attract new participants tend to stagnate; but communities that don't have a core of repeat participants tend to lose focus.

The existence of a certain community associated with each conference series that tends to repeat participation is clearly visible on the diagonal in Figure 10. The highest overlap of all in particular was between ICFP'16 and ICFP'17, with 180 repeaters. The four conference series show a healthy balance between repeat participation and newcomers.

The weaker overlap between conferences in different series is also apparent. For example, there is a somewhat surprising overlap between PLDI and POPL, followed by ICFP and POPL and by PLDI and SPLASH. The weakest overlaps are between ICFP and SPLASH, followed by ICFP and PLDI, and by POPL and SPLASH. It is unclear whether the overlap, or lack thereof, between these conference series is due to intellectual reasons or due to their dates. PLDI and POPL is the pair that is most distant in time, typically June and January, respectively. ICFP and



	ICFP10	ICFP11	ICFP12	ICFP13	ICFP14	ICFP15	ICFP16	ICFP17	ICFP18	PLDI9	PLDI13	PLDI14	PLDI15	PLDI16	PLDI17	PLDI18	POPL9	POPL11	POPL12	POPL13	POPL14	POPL15	POPL16	POPL17	POPL18	SPLASH9	SPLASH10	SPLASH12	SPLASH13	SPLASH14	SPLASH15	SPLASH16	SPLASH17
ICFP10	334	80	101	107	83	69	59	71	52	10	13	13	18	10	20	18	58	55	76	50	54	14	47	43	40	14	12	13	13	13	13	11	12
ICFP11		336	105	82	62	60	88	62	42	5	15	14	16	12	20	7	45	40	45	54	50	20	34	41	36	8	10	5	12	8	10	9	11
ICFP12			481	140	150	104	89	111	71	5	14	21	19	12	22	19	48	50	76	63	68	21	45	57	41	11	13	9	8	17	18	15	16
ICFP13				505	143	138	103	122	101	11	24	26	33	23	39	35	57	56	109	85	100	37	81	75	70	12	14	15	14	22	24	20	25
ICFP14					485	142	108	139	81	7	14	20	20	12	25	17	36	31	52	51	60	20	44	61	36	3	10	6	9	12	14	14	11
ICFP15						439	135	146	108	4	15	17	21	17	32	31	36	29	51	44	62	27	64	69	54	5	12	8	14	17	20	14	26
ICFP16							528	180	112	2	11	16	16	14	39	23	43	26	46	55	55	23	56	71	53	4	13	8	9	13	19	19	26
ICFP17								593	136	6	15	20	21	14	34	28	38	27	55	58	72	25	68	90	79	8	11	10	11	12	21	18	20
ICFP18									487	4	14	19	30	26	45	35	35	26	53	43	65	22	77	66	74	8	16	16	17	20	28	32	40
PLDI9										253	59	39	51	33	30	31	23	38	35	19	18	10	17	14	17	24	24	27	29	29	25	23	32
PLDI13											467	108	127	90	78	72	33	65	74	54	73	37	54	39	54	23	35	49	62	57	51	43	58
PLDI14												427	117	97	72	71	35	47	60	50	68	31	47	35	40	21	23	31	49	46	40	38	58
PLDI15													468	130	90	88	34	51	61	48	76	31	62	47	67	25	38	46	75	72	70	68	67
PLDI16														438	81	106	28	52	46	34	64	29	56	35	63	22	23	35	48	52	49	35	71
PLDI17															497	75	32	45	62	49	62	35	64	61	61	31	32	43	59	43	71	71	74
PLDI18																468	32	46	64	34	62	37	67	60	68	18	21	31	38	43	45	33	53
POPL9																	331	94	101	74	87	29	65	64	58	17	17	15	22	14	12	10	16
POPL11																		404	150	101	103	39	78	74	76	23	21	29	30	31	27	19	32
POPL12																			536	129	147	60	108	101	98	23	27	35	36	39	35	25	42
POPL13																				540	152	83	97	124	91	7	14	23	31	29	33	26	34
POPL14																					533	90	137	132	136	16	13	33	37	41	40	31	42
POPL15																						463	74	75	81	5	2	10	18	18	15	20	17
POPL16																							488	146	156	7	12	24	33	28	38	32	44
POPL17																								719	151	7	14	18	26	24	29	31	38
POPL18																									574	6	11	15	21	23	32	28	35
SPLASH9																										720	145	83	81	66	68	39	46
SPLASH10																											572	101	98	85	89	60	67
SPLASH12																												435	114	94	94	55	83
SPLASH13																													619	123	126	93	97
SPLASH14																														491	127	82	96
SPLASH15																															611	127	128
SPLASH16																																586	116
SPLASH17																																	582

Fig. 10. Conference participation overlap.

Conference	Avrg nb of participations	>= 2	>= 3	>= 4	>= 5
ALL	1.52	25.32	12.06	6.61	3.79
ICFP	1.64	28.86	14.39	8.9	5.45
POPL	1.59	27.98	14.04	7.87	4.79
PLDI	1.43	22.99	10.57	5.31	2.51
SPLASH	1.41	21.69	9.43	4.55	2.43

Table 11. Overall and for each conference, the average number of instances a participant has taken part of, and the percentage of them that has attended at least k instances, for $k \in [\![2 \dots 5]\!]$. Remark: the means and percentages are here computed with respect to *unique* participants.

SPLASH is the pair that is the closest in time, typically September and October. Time proximity may detract cross-participation.

Finally, Table 11 and 12 offer two different views on recurrent participation. Table 11 represents respectively for the whole dataset (row "ALL") and for each conference individually the average number of editions a participant has been part of, as well as the percentage of participants that have been part of at least a given number of editions of a conference. One striking fact is that no less than 75% of unique participants have been to just a single edition.

year	old timers
9	0.0
11	23.33
12	35.45
13	33.33
14	50.28
15	30.45
16	45.29
17	41.45
18	53.99

(a) Case of POPL

year	old timers
10	0.0
11	23.81
12	32.02
13	40.4
14	46.58
15	47.61
16	42.8
17	53.38
18	45.38

(b) Case of ICFP

year	old timers
9	0.0
13	12.63
14	27.87
15	38.28
16	43.84
17	33.94
18	40.17

(c) Case of PLDI

year	old timers
9	0.0
10	24.73
12	29.72
13	28.71
14	38.9
15	38.46
16	35.27
17	43.47

(d) Case of SPLASH

Table 12. For each conference, percentage of participants that have been part of a previous edition of the same conference

Table 12 is a normalization of the information represented in Figure 8: for each instance of each conference, it depicts the percentage of participants that have been part of a previous instance of the conference (in our dataset).

Observation 6. *Over all conferences, the average number of conferences a given participant has attended is just 1.52. Less than 4% of unique participants have been to more than five events among our dataset. Similarly, for any given event, more than half of the participants were experiencing this specific conference for the first time.*

5 A RETROSPECTIVE SPECULATION: PICKING THE OPTIMAL DESTINATION FOR PAST CONFERENCES

We have observed that the location an event takes place in significantly impacts the distribution of origin of its participants. However, setting this factor aside temporarily to consider what could have been the cheapest location for past conferences, assuming that the change in location would cause no change in participants, can be an illuminating exercise.

To this end, we chose a fixed number of locations that we believe to be representative and spread across the relevant parts of the globe: Paris, Edinburgh, Boston, Los Angeles, Vancouver, Tokyo, Beijing, and Mumbai. We then reprocessed the dataset to look for the location in this set that would have led to the lowest carbon footprint for each event, assuming that it would not have changed the set of participants.

Figure 13 depicts the resulting data: for each event, the best location and the average t_{CO_2e}it would have saved. We observe that in the majority of the events, the locality effect is strong enough that the optimal location is on

Event	Orig. Loc.	Orig. Cost	Best Loc.	Best Cost	Saved
ICFP 10	Baltimore	1.19	Philadelphia	1.18	0.01
ICFP 11	Tokyo	1.54	Tokyo*	1.54	0.0
ICFP 12	Copenhagen	0.88	Copenhagen*	0.88	0.0
ICFP 13	Boston	1.01	Boston*	1.01	0.0
ICFP 14	Gothenburg	0.88	Gothenburg*	0.88	0.0
ICFP 15	Vancouver	1.45	Philadelphia	1.37	0.08
ICFP 16	Nara	1.93	Edinburgh	1.9	0.03
ICFP 17	Oxford	1.03	Oxford*	1.03	0.0
ICFP 18	St. Louis	1.18	Philadelphia	1.12	0.06
POPL 9	Savannah	1.47	Boston	1.3	0.17
POPL 11	Austin	1.48	Philadelphia	1.27	0.21
POPL 12	Philadelphia	1.09	Philadelphia*	1.09	0.0
POPL 13	Rome	1.22	Paris	1.06	0.16
POPL 14	San Diego	1.7	Boston	1.24	0.46
POPL 15	Mumbai	1.62	Paris	1.59	0.03
POPL 16	St. Petersburg	1.43	Boston	1.14	0.29
POPL 17	Paris	0.93	Paris*	0.93	0.0
POPL 18	Los Angeles	1.62	Boston	1.3	0.32
PLDI 9	Dublin	1.5	Boston	1.22	0.28
PLDI 13	Seattle	1.27	Seattle*	1.27	0.0
PLDI 14	Edinburgh	1.28	Edinburgh*	1.28	0.0
PLDI 15	Portland	1.29	Philadelphia	1.14	0.15
PLDI 16	Santa Barbara	1.31	Philadelphia	1.2	0.11
PLDI 17	Barcelona	1.59	Edinburgh	1.42	0.17
PLDI 18	Philadelphia	0.9	Philadelphia*	0.9	0.0
SPLASH 9	Reno	1.59	Philadelphia	1.19	0.4
SPLASH 10	Sparks	1.45	Philadelphia	1.29	0.16
SPLASH 12	Tucson	1.53	Philadelphia	1.28	0.25
SPLASH 13	Indianapolis	1.1	Philadelphia	1.09	0.01
SPLASH 14	Portland	1.27	Philadelphia	1.22	0.05
SPLASH 15	Pittsburgh	1.27	Pittsburgh*	1.27	0.0
SPLASH 16	Amsterdam	1.02	Amsterdam*	1.02	0.0
SPLASH 17	Vancouver	1.49	Philadelphia	1.33	0.16

Table 13. For each event, depicts the location among Paris, Edinburgh, Boston, Philadelphia, Los Angeles, Vancouver, Tokyo, Beijing and Mumbai that would have led to the lowest carbon footprint. Starred best locations indicates that they coincide with the original one. The final column shows the amount of t_{CO_2e}that it would have saved.

the same continent as the actual location. However, it is striking to see how often the east coast of the US turns out to be the cheapest destination. In particular, it appears to be preferable to the west coast in most cases (in spite of the underlying locality effect that we are ignoring here).

Observation 7. *Due to the locality effect, past data can act as a heuristic for a worst case distribution of attendance with respect to the objective function of minimizing the carbon footprint. Doing so most notably suggests that the east coast of the US is generally a lower-carbon location than the west coast for these conferences.*

6 AN OPEN SOURCE TOOL FOR SIMILAR ANALYSES

We hope that the analysis we have conducted for a few SIGPLAN conferences will offer valuable insights for the organizers of these conferences. Clearly, though, any observations based on our data cannot be taken as universal facts: the situation heavily depends notably on the geographical distribution of the underlying research community and on its cultural habits of attendance. Moreover, the practical conclusions that it should entail may diverge from one community to another. Accordingly, we strongly encourage similar studies to be performed by other groups.

To help with this, we have developed an open source Python 3 script that we intend to be as parameterizable and reusable as possible. All analyses presented in this paper have been generated using this tool[4]. The script can be found at the following github repository: https://github.com/YaZko/acm-climate. We welcome all remarks, pull requests, feature requests and would be happy to assist anyone wishing to use the tool for their own analysis.

A more detailed documentation is available in the repository. We give here a high-level overview of its content.

The script requires as an input a dataset similar to ours, described by two `csv` files. The first one describes the list of conferences: each line describes a specific event and the location it took place in, i.e. has the fields `Name, Year, City, State` and `Country`. The second one contains the list of participants of these events: each line describes a unique participation at an event with the location of origin of the participant, i.e. has the fields `Identifier, City, State, Country, Conference` and `Year`.

The first pass of the analysis computes the needed raw data. Informal named locations manually provided by participant are mapped to their ISO designation using the `pycountry` library. Once this is done, these named locations are converted to GPS locations using the `geopy` library, which provides a straightforward API to do this. To avoid duplicating requests to online APIs, all of these computations are cached locally.

Distances in kilometers between locations are then computed between GPS locations once again using the `geopy` library. They use the geodesic distance (shortest distance for an ellipsoidal model of the Earth) with a model providing precision that is several orders more precise than we need.

At this point, we therefore know, for each participant in a conference, the distance they traveled. The script then uses a model that computes the carbon cost of air travel based on this information. For the analysis presented in this paper, we used the `DEFRA 16` model described in Section 3.1, but we are also experimenting with a similar one developed by `CoolEffect`[5]. As long as models are functions of the distance, more can be easily added.

This first pass of the script therefore gives us an estimate of the footprint of our conferences. We have implemented on top of it all the analyses that we described through Section 4, as well as the speculative analysis described in Section 5. The output of these analyses is encoded into `csv` tables that can be used as-is or as the basis of visualization exercises.

There are room for improvement on pretty much all sides: footprint models to be experimented, more complex analyses to be performed or automating the visualization of the data to cite just a few. But we hope that this preliminary tool will form the basis for fruitful discussion as it grows to address the needs of more research communities.

7 CONCLUSION

Carbon footprint is becoming a significant consideration for conference organizers. To support effective decision-making, we have conducted an analysis of the participation for several SIGPLAN conferences, drawing both an estimate of their carbon footprint and various correlations between the geographical distribution of its attendees and this footprint.

[4]The graphical visualizations have been made separately, the script currently only generates tables. Extending it to generate graphical takes on these tables would be an interesting feature.
[5]https://www.cooleffect.org/

We believe that the experiment we conducted in this paper should be generalized. To help move toward this goal, as well as to trigger debates over the right way to conduct these analyses, we developed a reusable, open source tool allowing others to easily conduct similar experiments.

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