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2 ABSTRACT

- 3 Abstract length and content varies depending on article type. Refer to http://
- 4 www.frontiersin.org/about/AuthorGuidelines for abstract requirement and length
- 5 according to article type.

1 INTRODUCTION

7 Hello, how are we doing?

2 METHODS

8 **2.1 Clean up**

- 9 All functional annotation sets were cleaned up the following way (using definitions from the Gene
- 10 Ontology version 2019-07-01):
- 1. Any annotations where the GO accession was marked as obsolete were removed.
- 12 2. Some terms in the GO have 'alternative ids'. When naively removing duplicates, two entries will not
- be recognized as duplicates if they have different accessions pointing to the same GO term. Therefore,
- all GO accessions were changed to their respecitve 'main id' and the dataset was again scanned for
- duplicates.
- Table 1 provides information on the number of annotations that were removed this way from each dataset.
- 17 All further analyses were performed on the cleaned datasets since we assume the user will only be interested
- 18 in still valid and non-redundant functional annotations.

19 2.2 Choosing the right evaluation metric

- 20 A plethora of different metric to evaluate the quality of functional annotation predictions is available using
- 21 different approaches and there seems to be no clear standard yet. TODO: THIS IS WEAK Additionally,

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Table 1. Number of removed annotations during cleanup.

Genome	Dataset	Obsolete Annotations	Duplicates
Brachypodium distachyon	GOMAP	696	43
Gossypium raimondii	GOMAP	184	0
Hordeum vulgarum	GoldStandard	0	4
Medicago truncatula A17	GOMAP	0	0
Medicago truncatula R108	GOMAP	0	0
Oryza sativa	GOMAP GoldStandard Gramene61-IEA	111 38 10	2 556 14
Phaseolus vulgaris	GOMAP	0	0
Sorghum bicolor	GOMAP	690	59
Triticum aestivum	GOMAP GoldStandard Gramene61-IEA	285 0 47	0 10 48
Vigna unguiculata	GOMAP	0	0
Zea mays B73.v3	GOMAP GoldStandard Gramene49 Phytozome	1107 1 94 54	70 0 2 0
Zea mays B73.v4	GOMAP GoldStandard Gramene61-IEA	752 55 99	83 174 157
Zea mays Mo17	GOMAP	726	77
Zea mays PH207	GOMAP	798	76
Zea mays W22	GOMAP	754	82

22 each of the metrics has a different focus and lalala so choosing a metric for quality evaluation is not trivial. When we first published GOMAP (Wimalanathan et al., 2018), we used a modified version of the hierarchical evaluation metrics originally introduced in (Verspoor et al., 2006) because they were simple, clear, and part of an earlier attempt at unifying and standardizing GO annotation comparisons (Defoin-Platel et al., 2011). In the meantime, Plyusnin et al. (2018) have published an approach for evaluating different metrics showing substantial differences within the robustness of different approaches. TODO DESCRIBE THEIR APPROACH We have applied their method on the Gold Standards available to us to determine which evaluation metric is the most appropriate in our case. The results of this analysis can be seen in

We then evaluated our predictions and the other annotation sets using the best performing metrics as well as the one we previously used. TODO

3 **RESULTS**

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33 ... a quantitative comparison of the datasets in Table.

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Table 2. Quantitative metrics of the cleaned functional annotation sets. CC, BF, MP, and A refer to the aspects of the GO: Cellular Component, Biological Function, Molecular Process, and Any/All.

				Genes Ann	notated[%]a			Anno	tations ^b		Med	ian A	nn. pei	r G.c
Genome	Genes	Dataset	CC	BF	MP	A	CC	BF	MP	A	CC	BF	MP	A
Arachis hypogaea	67,124	GOMAP	85.91	84.70	100.00	100.00	153,433	132,944	493,799	780,176	2	2	6	10
Brachypodium distachyon	100	GOMAP	27,923.00	29,292.00	34,309.00	34,310.00	75,877	69,709	255,807	401,393	2	2	6	10
Glycine max	52,872	GOMAP	87.04	88.96	100.00	100.00	129,215	113,827	417,555	660,597	2	2	6	11
Gossypium raimondii	100	GOMAP	34,908.00	34,651.00	37,504.00	37,505.00	96,793	85,511	307,921	490,225	2	2	6	11
Hordeum vulgarum	39,734	GOMAP GoldStandard	88.68 0.02	91.79 0.05	100.00 0.05	100.00 0.07	88,130 7	80,282 23	272,823 45	441,235 75	2 0	2	5 1	10 2
Medicago truncatula A17	50,444	GOMAP	83.90	86.70	100.00	100.00	107,362	99,719	364,065	571,146	2	2	6	10
Medicago truncatula R108	55,706	GOMAP	72.40	90.15	100.00	100.00	112,343	108,031	382,322	602,696	1	2	5	9
Oryza sativa	35,825	GOMAP GoldStandard Gramene61-IEA	79.89 15.98 30.07	83.33 20.61 43.37	100.00 25.21 46.63	100.00 31.79 59.86	72,780 7,730 14,633	64,685 11,060 32,787	248,700 19,378 39,105	386,165 38,176 86,529	2 1 1	2 1 1	6 1 1	9 3 3
Phaseolus vulgaris	27,433	GOMAP	94.54	93.10	100.00	100.00	72,005	64,583	229,630	366,218	2	2	6	11
Sorghum bicolor	100	GOMAP	28,154.00	29,353.00	34,128.00	34,129.00	76,689	70,190	259,413	406,292	2	2	6	10
Triticum aestivum	107,891	GOMAP GoldStandard Gramene61-IEA	88.61 0.89 26.74	91.01 0.57 55.24	100.00 1.54 48.72	100.00 1.73 70.24	267,741 1,590 38,975	218,623 923 109,319	785,960 4,807 109,518	1,272,324 7,323 257,832	1 0	2 0 1	6 2 1	10 3 2
Vigna unguiculata	29,773	GOMAP	91.27	91.10	100.00	100.00	75,867	68,313	243,278	387,458	2	2	6	11
Zea mays B73.v3		GOMAP GoldStandard Gramene49 Phytozome GOMAP	34,866.00 1,548.00 11,834.00 4,524.00 36,717.00	38,073.00 60.00 17,991.00 13,728.00 37,337.00	39,468.00 151.00 15,800.00 11,365.00 39,323.00	39,469.00 1,634.00 21,926.00 16,132.00 39,324.00	135,211 1,565 20,072 4,787 88,827	87,420 65 31,056 19,044 82,251	291,251 299 30,089 13,100 278,719	513,882 1,929 81,217 36,931 449,797	3 1 1 0 2	2 0 1 1 2	6 0 1 1 6	11 1 3 2 10
Zea mays B73.v4 Zea mays Mo17	100	GoldStandard Gramene61-IEA GOMAP	8,349.00 14,774.00 33,618.00	10,067.00 22,064.00 35,105.00	12,120.00 23,965.00 38,619.00	14,971.00 29,152.00 38,620.00	11,510 20,265 87,567	15,019 47,657 79,214	25,737 58,110 277,787	52,428 126,525 444,568	1 1	1 1 2	1 2 6	3 3 10
Zea mays PH207 Zea mays W22		GOMAP GOMAP	35,170.00 36,987.00	36,762.00 37,685.00	40,556.00 40,689.00	40,557.00 40,690.00	90,617 95,390	85,500 85,039	288,677 289,780	464,794 470,209	2 2 2	2 2	6	10 10 10

 $[\]begin{tabular}{ll} \hline a How many genes in the genome have at least one GO term from the CC, BF, MP aspect annotated to them? A = How many at least one from any aspect? (A = CC <math>\cup$ BF \cup MP) \\ \hline \$a\$ How many genes in the genome have at least one GO term from the CC, BF, MP aspect annotated to them? A = How many at least one from any aspect? (A = CC \cup BF \cup MP) \\ \hline \$a\$ How many genes in the genome have at least one GO term from the CC, BF, MP aspect annotated to them? A = How many at least one from any aspect? (A = CC \cup BF \cup MP) \\ \hline \$a\$ How many genes in the genome have at least one GO term from the CC, BF, MP aspect annotated to them? A = How many at least one from any aspect? (A = CC \cup BF \cup MP) \\ \hline \$a\$ How many genes in the general properties of the context o

Table 3. Quality evaluation of the used GO annotation sets.

Genome	Dataset	SimGIC2 score	TC AUCPCR score
Hordeum vulgarum	GOMAP	0.158996	0.000477
Oryza sativa	GOMAP	0.253680	0.204084
	Gramene61-IEA	0.330437	0.193740
Triticum aestivum	GOMAP	0.218996	0.010039
	Gramene61-IEA	0.175564	0.005397
Zea mays B73.v3	GOMAP	0.052182	0.012709
	Gramene49	0.091475	0.019127
	Phytozome	0.028721	0.004498
Zea mays B73.v4	GOMAP	0.257543	0.196845
	Gramene61-IEA	0.328777	0.188584

3.1 Quality Evaluation 34

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TODO If it turns out that our predictions are good with hF but bad with more approriate metrics, explanation would be that score thresholds for the prediction tools used in the GOMAP pipeline have been chosen to maximize this hF value. It now seems reasonable to re-adjust these thresholds to maximize a different metric which will likely result in a drop in hF score but increase in other metrics. Again emphasizes the importance of choosing the right evaluation metric.

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b How many annotations in the CC, BF, and MP aspect does this dataset contain? A = How many in total? A = CC + BF + MP

c Take a typical gene that is present in the annotation set. How many annotations does it have in each aspect? A = How many in total? Ask your favorite statistician why $A \neq CC + BF + MP$

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