

Article Title

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2 ABSTRACT

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Keywords: Text Text Text Text Text Text Text Text

1 INTRODUCTION

Hello, how are we doing?

2 METHODS

2.1 Generating Predictions

Used GOMAP on condo lalala. Input files are (usually) published along results.

2.2 Clean up

All functional annotation sets were cleaned up the following way (using definitions from the Gene Ontology version 2019-07-01):

1. Any annotations where the GO accession was marked as obsolete were removed.
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 respective '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. All further analyses were performed on the cleaned datasets since we assume the user will only be interested in still valid and non-redundant functional annotations.

2.3 Quantitative Evaluation

lalala lololo table xyz

2.4 Quality Evaluation

Quality evaluation of gene function predictions is not trivial and usually done by comparing the set of predicted functions of a gene against a *gold standard* consisting of annotations that are assumed to be correct. We used annotations that were created or in some way curated with human participation for gold standards. There are a plethora of different metrics to perform the comparison of predictions against this gold standard. 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 TODO.

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

2.5 Phylogenetic Tree Construction

To demonstrate that a more top-level and holistic use of whole-genome functional predictions can still be useful we devised some simple ways of applying phylogenetic methods to our predictions. ### Distance Based ### Character Based

2.6 Ensuring Reproducibility

containerization, github...

3 RESULTS

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

3.1 Quality Evaluation

TODO If it turns out that our predictions are good with hF but bad with more appropriate 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. Also shows how comparison between different pipelines/predictions can be difficult if chose different metric or optimized for different metric. Also: if an annotation is not present in the gold standard, there is no way of knowing whether that gene truly doesn't have that function or whether it has just never been characterized/examined. So we cannot distinguish between a biologically true negative and an actually false negative in the gold standard. This poses a problem when annotations are predicted that are not found in the gold standard: Is this truly a wrong prediction or is the gold standard incomplete? Especially in our case where the predictions not only contain more annotations than the gold standard, but are also more diverse. In effect this means that a quality

Table 1. Number of removed annotations during cleanup.

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

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score as calculated above may not only describe the quality of the prediction, but to some extent also the completeness of the gold standard itself. At least we can see here that gold standards with a median of 3 annotations per gene resulted in higher quality scores than gold standards with less annotations per gene, even though predictions were generated the same way in all cases. TODO maybe put a figure with regression quality score/median annotations per gene or something In conclusion this means that truly making a statement about the quality of a prediction set would require the ideal and complete gold standard. The scores we can generate so far are by far not as meaningful.

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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.

Genome	Genes	Dataset	Genes Annotated[%] ^a				Annotations ^b				Median Ann. per G. ^c			
			CC	BF	MP	A	CC	BF	MP	A	CC	BF	MP	A
<i>Arachis hypogaea</i>	67,124	GOMAP	85.91	84.70	100.00	100.00	153,433	132,944	493,799	780,176	2	2	6	10
<i>Brachypodium distachyon</i>	34,310	GOMAP	81.38	85.37	100.00	100.00	75,877	69,709	255,807	401,393	2	2	6	10
<i>Glycine max</i>	52,872	GOMAP	87.04	88.96	100.00	100.00	129,215	113,827	417,555	660,597	2	2	6	11
<i>Gossypium raimondii</i>	37,505	GOMAP	93.08	92.39	100.00	100.00	96,793	85,511	307,921	490,225	2	2	6	11
<i>Hordeum vulgare</i>	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 1	5 1	10 2
<i>Medicago truncatula</i> A17	50,444	GOMAP	83.90	86.70	100.00	100.00	107,362	99,719	364,065	571,146	2	2	6	10
<i>Medicago truncatula</i> R108	55,706	GOMAP	72.40	90.15	100.00	100.00	112,343	108,031	382,322	602,696	1	2	5	9
<i>Oryza sativa</i>	35,825	GOMAP	79.89	83.33	100.00	100.00	72,780	64,685	248,700	386,165	2	2	6	9
		GoldStandard	15.98	20.61	25.21	31.79	7,730	11,060	19,378	38,176	1	1	1	3
		Gramene61-IEA	30.07	43.37	46.63	59.86	14,633	32,787	39,105	86,529	1	1	1	3
<i>Phaseolus vulgaris</i>	27,433	GOMAP	94.54	93.10	100.00	100.00	72,005	64,583	229,630	366,218	2	2	6	11
<i>Sorghum bicolor</i>	34,129	GOMAP	82.49	86.01	100.00	100.00	76,689	70,190	259,413	406,292	2	2	6	10
<i>Triticum aestivum</i>	107,891	GOMAP	88.61	91.01	100.00	100.00	267,741	218,623	785,960	1,272,324	2	2	6	10
		GoldStandard	0.89	0.57	1.54	1.73	1,590	923	4,807	7,323	1	0	2	3
		Gramene61-IEA	26.74	55.24	48.72	70.24	38,975	109,319	109,518	257,832	0	1	1	2
<i>Vigna unguiculata</i>	29,773	GOMAP	91.27	91.10	100.00	100.00	75,867	68,313	243,278	387,458	2	2	6	11
<i>Zea mays</i> B73.v3	39,469	GOMAP	88.34	96.46	100.00	100.00	135,211	87,420	291,251	513,882	3	2	6	11
		GoldStandard-OFF	3.92	0.15	0.38	4.14	1,565	65	299	1,929	1	0	0	1
		Gramene49	29.98	45.58	40.03	55.55	20,072	31,056	30,089	81,217	1	1	1	3
		Phytozome	11.46	34.78	28.79	40.87	4,787	19,044	13,100	36,931	0	1	1	2
<i>Zea mays</i> B73.v4	39,324	GOMAP	93.37	94.95	100.00	100.00	88,827	82,251	278,719	449,797	2	2	6	10
		GoldStandard	21.23	25.60	30.82	38.07	11,510	15,019	25,737	52,428	1	1	1	3
		Gramene61-IEA	37.57	56.11	60.94	74.13	20,265	47,657	58,110	126,525	1	1	2	3
<i>Zea mays</i> Mo17	38,620	GOMAP	87.05	90.90	100.00	100.00	87,567	79,214	277,787	444,568	2	2	6	10
<i>Zea mays</i> PH207	40,557	GOMAP	86.72	90.64	100.00	100.00	90,617	85,500	288,677	464,794	2	2	6	10
<i>Zea mays</i> W22	40,690	GOMAP	90.90	92.61	100.00	100.00	95,390	85,039	289,780	470,209	2	2	6	10

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^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 ∪ BF ∪ MP)^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? Please note that A ≠ CC + BF + MP**Table 3.** Quality evaluation of the used GO annotation sets.

Genome	Dataset	SimGIC2			TC-AUCPCR		
		CC	MF	BP	CC	MF	BP
<i>Hordeum vulgare</i>	GOMAP	0.309334	0.424286	0.180110	NaN	0.000492	0.000388
<i>Oryza sativa</i>	GOMAP	0.498631	0.454389	0.213624	0.272899	0.268926	0.141812
	Gramene61-IEA	0.416283	0.415342	0.324981	0.170662	0.257685	0.126104
<i>Triticum aestivum</i>	GOMAP	0.473080	0.417054	0.202375	0.014552	0.005456	0.009284
	Gramene61-IEA	0.384973	0.346840	0.191962	0.004446	0.006115	0.004811
<i>Zea mays</i> B73.v4	GOMAP	0.498574	0.434275	0.212010	0.274600	0.249346	0.133593
	Gramene61-IEA	0.368491	0.411399	0.323139	0.159213	0.229186	0.130063

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