“ It’s a Match! ”
A Benchmark of Task Affinity Scores for Joint Learning
Supplementary Material

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Abstract

The following elements are provided in the supplementary material:

1. Affinity scores raw values
2. Taskonomy buildings used
3. Affinity scores computation

1 Affinity scores raw values

In Tables 1 to 6, we report the raw affinities estimations for all tasks, using each affinity scoring technique. Results are rounded at the second decimal.

	Affinities estimations				
with	**SemSeg**	**Keypts**	**Edges**	**Depth**	**Normal**
SemSeg	-	-8	-6	-8	-5
Keypts	-8	-	-4	-12	-9
Edges	-6	-4	-	-10	-7
Depth	-8	-12	-10	-	-5
Normal	-5	-9	-7	-5	-

Table 1: *Taxonomical distance (TD).* Distance between tasks in the similarity tree from (Zamir et al. 2018). Multiplied by -1 for consistency (i.e., higher means more affinity).

	Affinities estimations				
with	**SemSeg**	**Keypts**	**Edges**	**Depth**	**Normal**
SemSeg	-	0.25	0.23	0.31	0.45
Keypts	0.25	-	0.52	0.18	0.23
Edges	0.23	0.52	-	0.18	0.22
Depth	0.31	0.18	0.18	-	0.29
Normal	0.45	0.23	0.22	0.29	-

Table 2: *Input attribution similarity (IAS).* Cosine similarity between STL models attribution maps.

	Affinities estimations				
with	**SemSeg**	**Keypts**	**Edges**	**Depth**	**Normal**
SemSeg	-	0.33	0.37	0.46	0.46
Keypts	0.33	-	0.66	0.04	0.05
Edges	0.37	0.66	-	0.12	0.13
Depth	0.46	0.04	0.12	-	0.69
Normal	0.46	0.05	0.13	0.69	-

Table 3: *Representation similarity analysis (RSA).* Representation similarity analysis using the STL models backbones output.

	Affinities estimations				
with	**SemSeg**	**Keypts**	**Edges**	**Depth**	**Normal**
SemSeg	-	-2.93	-3.50	-3.07	+3.70
Keypts	-8.47	-	+4.97	-8.31	+1.42
Edges	-15.93	-4.20	-	-9.58	+2.42
Depth	+4.04	-3.34	-1.26	-	+20.29
Normal	+25.68	+60.29	+23.79	+66.30	-

Table 4: *Label injection (LI).* Performance gain (%) when incorporating the label from the partner task in the STL model’s input, relative to standard STL.

	Affinities estimations				
with	**SemSeg**	**Keypts**	**Edges**	**Depth**	**Normal**
SemSeg	-	0.51	0.39	1.93	1.54
Keypts	0.51	-	1.89	0.75	1.0
Edges	0.39	1.89	-	0.92	0.59
Depth	1.93	0.75	0.92	-	8.40
Normal	1.54	1.0	0.59	8.40	-

Table 5: *Gradient similarity (GS).* Cosine similarity between task-specific gradient updates on the MTL backbone. Averaged across all training epochs. Multiplied by 100.

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with	Affinities estimations				
	SemSeg	**Keypts**	**Edges**	**Depth**	**Normal**
SemSeg	-	+0.02	+0.25	+1.69	+0.74
Keypts	-0.03	-	+0.38	-0.01	+0.01
Edges	-0.20	+0.71	-	+0.19	+0.27
Depth	+0.47	+0.01	+0.15	-	+0.90
Normal	+0.27	+0.03	+0.16	+1.26	-

Table 6: *Gradient transference (GT).* Look-ahead ratio simulating the effect of applying task-specific updates to the MTL backbone for the other task. Averaged across all training epochs.

2 Taskonomy buildings used

We split our subset of the Taskonomy dataset into train, validation and test sets, on a per-building basis.

Train set These buildings amount to 603,437 input images.

- adairsville
- airport
- albertville
- anaheim
- ancor
- andover
- annona
- arkansaw
- athens
- bautista
- bohemia
- bonesteel
- bonnie
- broseley
- browntown
- byers
- scioto
- nuevo
- goodfield
- donaldson
- hanson
- merom
- klickitat
- onaga
- leonardo
- marstons
- newfields
- pinesdale
- lakeville
- cosmos
- benevolence
- pomaria
- tolstoy
- shelbyville
- allensville
- wainscott
- beechwood
- coffeen
- stockman
- hiteman
- woodbine
- lindenwood
- forkland
- mifflinburg
- ranchester
- springerville
- swisshome
- westfield
- willow
- winooski
- hainesburg
- irvine
- pearce
- thrall
- tilghmanton
- uvalda
- sugarville
- silas

Validation set These buildings amount to 82,345 input images.

- corozal
- collierville
- markleeville
- darden
- chilhowie
- churchton
- cauthron
- cousins
- timberon
- wando

Test set These buildings amount to 40,367 input images.

- ihlen
- muleshoe
- noxapater
- mcdade

Affinity scoring	Type	Computation	Comment	Range
Taxonomical distance (TD)	Model-agnostic	Distance between tasks in a taxonomy tree.	Symmetric. Taxonomy borrowed from (Zamir et al. 2018). Multiplied by -1 for consistency i.e., higher is better.	$]-\infty, 0]$
Input attribution similarity (IAS)	STL-based	$\frac{1}{\lvert\mathcal{X}\rvert}\sum_{x\in\mathcal{X}} S_{cos}(Attr(STL_a, x), Attr(STL_b, x)),$ (1) where S_{cos} is cosine similarity, $\mathcal{X}$ denotes a batch of examples and $Attr$ the attribution method used.	Symmetric. Revisited from (Song et al. 2019). Computed on a subset of the test set (2,048 images) using $InputXGradient$ attribution (Shrikumar et al. 2016).	$[-1, +1]$
Representation similarity analysis (RSA)	STL-based	$RSA(\theta_{Ba}, \theta_{Bb}, \mathcal{X}),$ (2) where RSA denotes the Representation Similiarity Analysis, $\mathcal{X}$ a batch of examples, θ_{Ba} and θ_{Bb} the backbone weights of the STL models for tasks a and b resp.	Symmetric. Revisited from (Dwivedi and Roig 2019). Computed on a subset of the test set (2,048 images).	$[-1, +1]$
Label injection (LI)	STL-based	$\frac{\mathcal{L}_{STL_a} - \mathcal{L}_{STL_{a\leftarrow b}}}{\mathcal{L}_{STL_{a\leftarrow b}}},$ (3) where $STL_{a\leftarrow b}$ represents the STL model for task a, modified to ingest the corresponding label from task b in addition to the input.	Asymmetric. Novel proposal. Computed using test losses.	$]-\infty, +\infty[$
Gradient similarity (GS)	MTL-based	$\frac{1}{N}\sum_{i=1}^{N} S_{cos}(\frac{\partial\mathcal{L}_a(\mathcal{X}, \theta^i_B, \theta^i_{Ha})}{\partial\theta^i_B}, \frac{\partial\mathcal{L}_b(\mathcal{X}, \theta^i_B, \theta^i_{Hb})}{\partial\theta^i_B}),$ (4) where N denotes the number of training epochs, S_{cos} the cosine similarity, $\mathcal{X}$ a batch of examples, θ^i_B the weights of the common MTL backbone at the ith epoch, θ^i_{Ha} and θ^i_{Hb} the weights of the heads for a and b at the ith epoch.	Symmetric. Borrowed from (Fifty et al. 2021; Zhao et al. 2018).	$[-1, +1]$
Gradient transference (GT)	MTL-based	$\frac{1}{N}\sum_{i=1}^{N} 1 - \frac{\mathcal{L}_a(\mathcal{X}, \theta^{i+1}_{B\lvert b}, \theta^i_{Ha})}{\mathcal{L}_a(\mathcal{X}, \theta^i_B, \theta^i_{Ha})},$ (5) where N denotes the number of training epochs, $\mathcal{X}$ a batch of examples, $\theta^{i+1}_{B\lvert b}$ the weights of the common MTL backbone updated using the loss of task b at the epoch $i+1$, θ^i_{Ha} and θ^i_{Hb} the weights of the heads for a and b at the ith epoch.	Asymmetric. Borrowed from (Fifty et al. 2021).	$]-\infty, +\infty[$

Table 7: Tasks affinity scores description and computation considering two tasks $t_1 = a$ and $t_2 = b$.

3 Affinity scores computation

In Table 7, we detail the computation of each selected affinity score. Considering two tasks $t_1 = a$ and $t_2 = b$ and a batch of examples $\mathcal{X}$, we denote:

- their resp. losses functions $\mathcal{L}_a$ and $\mathcal{L}_b$
- their resp. STL models STL_a and STL_b with losses
  - $\mathcal{L}_{STL_a} = \mathcal{L}_a(\mathcal{X}, STL_a)$
  - $\mathcal{L}_{STL_b} = \mathcal{L}_b(\mathcal{X}, STL_b)$
- their joint MTL model $MTL_{(a,b)}$ with loss $\mathcal{L}_{MTL_{(a,b)}} = \mathcal{L}_a(\mathcal{X}, MTL_{(a,b)}) + \mathcal{L}_b(\mathcal{X}, MTL_{(a,b)})$

Note that if the score is symmetric, it assesses how much the two tasks help each other regardless of direction. If it is asymmetric, it considers how much the target task a benefits from being learned with the partner task b. While all scores could not be constrained to lie in the same range, higher always means more affinity.

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