1 Mathematical details

We provide some mathematical details for which we did not have enough space in the main paper.

1.1 Expression for the gradient of multiclass logistic regression (Equations 6 and 7)

For multiclass logistic regression, the loss function is:

$$L_S(\phi, V) = \frac{1}{|S|} \sum_{(x,y) \in S} L_{cls}(V, \phi(x), y) \tag{1}$$

$$L_{cls}(V, \phi(x), y) = -\log p_y(V, \phi(x)) \tag{2}$$

$$p_k(V, \phi(x)) = \frac{\exp(v_k^T \phi(x))}{\sum_j \exp(v_j^T \phi(x))} \tag{3}$$

Let us first calculate the gradient of p_k w.r.t each v_j :

$$\nabla_{v_j} p_k(V, \phi(x)) = \frac{\exp(v_k^T \phi(x)) \delta_{jk} \phi(x)}{\sum_j \exp(v_j^T \phi(x))} - \frac{\exp(v_k^T \phi(x)) \exp(v_j^T \phi(x)) \phi(x)}{(\sum_j \exp(v_j^T \phi(x)))^2} \tag{4}$$

$$= (p_k(V, \phi(x)) \delta_{kj} - p_k(V, \phi(x)) p_j(V, \phi(x))) \phi(x) \tag{5}$$

The gradient of $L_{cls}(V, \phi(x), y)$ w.r.t v_j is then:

$$\nabla_{v_j} L_{cls}(V, \phi(x), y) = -\frac{1}{p_y(V, \phi(x))} \nabla_{v_j} p_y(V, \phi(x)) \tag{6}$$

$$= -\frac{1}{p_y(V, \phi(X))} (p_y(V, \phi(x)) \delta_{yj} - p_y(V, \phi(x)) p_j(V, \phi(x))) \phi(x) \tag{7}$$

$$= (p_j(V, \phi(x)) - \delta_{yj}) \phi(x) \tag{8}$$

The gradient of $L_S(\phi, V)$ w.r.t v_j is therefore:

$$\nabla_{v_j} L_S(\phi, V) = g_j(S, V) = \frac{1}{|S|} \sum_{(x,y) \in S} (p_j(V, \phi(x)) - \delta_{yj}) \phi(x) \tag{9}$$

thus leading to Equations 6 and 7 in the main paper.

1.2 Proof that $\alpha(W, \phi(x), y) \in [0, 2]$:

Recall that $\alpha(W, \phi(x), y) = \sum_k (p_k(W, \phi(x)) - \delta_{yk})^2$. Since it is a sum of squares, $\alpha(W, \phi(x), y) \geq 0$. Further,

$$\sum_k (p_k(W, \phi(x)) - \delta_{yk})^2 = \sum_k p_k(W, \phi(x))^2 + \sum_k \delta_{yk}^2 - 2\sum_k \delta_{yk} p_k(W, \phi(x)) \tag{10}$$

$$\leq \sum_k p_k(W, \phi(x))^2 + \sum_k \delta_{yk}^2 \tag{11}$$

$$\leq \sum_k p_k(W, \phi(x)) + \sum_k \delta_{yk} \tag{12}$$

$$= 2 \tag{13}$$

where the first inequality uses the fact that both p_k and δ_{yk} are positive, and the second inequality uses the fact that both p_k and δ_{yk} are less than or equal to 1.

2 Improvement vs similarity between base and novel categories

Our analogy-based hallucination strategy is based on the intuition that modes of variation are shared. However, this may not be true for novel categories that are very different from all the base classes. Here, we see if our hallucination strategy still provides useful gains for such categories.

We quantified the similarity between a novel category and the set of base categories by measuring how far up the ImageNet tree we need to go before encountering an ancestor of a base class. For convenience, we call this the "tree distance". Figure 1 shows how the top-5 accuracy gains we get (with $n = 1$ examples per novel class) from hallucination varies with the tree distance of the novel category from base classes. As expected, we find that average gains are larger when the tree distance is lower. However, the fraction of classes seeing large gains (greater than 25 points) remains about the same for a tree distance of 1, 2 or 3 before decreasing quickly. Thus, while similar classes gain more, gains do carry over to categories quite far off from the base classes.

3 Numerical results

Tables 1 and 2 show the numerical top-1 accuracy on novel classes and all classes respectively. Note that some methods such as Model Regression [3] and Matching Networks [2] improve the top-1 accuracy for novel classes, but this seems to be at the expense of base classes, resulting in a lower accuracy when measured on all classes taken together.

Standard deviations for the accuracies are shown in Tables 3, 4, 5 and 6. Most of these values are less than 0.5 points.

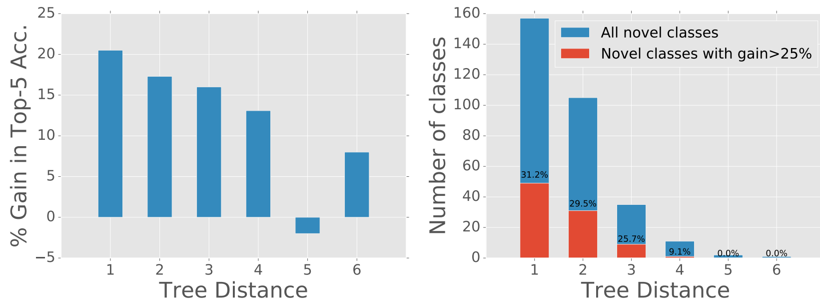

Figure 1: (Left) Average gain in top-5 accuracy ($n = 1$) vs tree distance. (Right) The number of novel categories that see at least a 25 point gain (absolute) compared to the total number of novel categories, vs tree distance. Numbers on the bars indicate the percentage of classes that see a 25 point gain.

Representation	Lowshot phase	n=1	2	5	10	20
Baseline	Classifier	2.77	10.78	26.38	35.46	41.49
Baseline	Generation* + Classifier	9.17	15.85	25.47	33.21	40.41
SGM*	Classifier	4.14	13.08	27.83	36.04	41.36
SGM*	Generation* + Classifier	9.85	17.32	27.89	36.17	41.42
Batch SGM*	Classifier	4.16	13.01	28.12	36.56	42.07
Triplets	Classifier	6.22	15.13	24.58	28.73	31.14
L2*	Classifier	7.14	16.75	27.73	32.32	35.11
Dropout	Classifier	7.22	16.58	27.77	33.28	36.80
Decov	Classifier	1.75	8.83	26.52	36.33	41.87
L1*	Classifier	4.88	14.40	28.54	35.59	39.90
Multiverse	Classifier	1.55	6.47	19.93	31.04	39.65
Baseline	Model Regression	5.73	15.62	30.53	38.25	43.57
Baseline	Matching Network	18.33	23.87	31.08	35.27	38.45
Baseline-ft	Classifier	2.26	8.52	23.97	34.42	40.96
Baseline (Resnet 50)	Classifier	6.82	18.37	36.55	46.15	51.99
Baseline (Resnet 50)	Generation* + Classifier	16.58	25.38	36.16	44.53	52.06
SGM (Resnet 50)	Classifier	10.23	21.45	37.25	46.00	51.83
SGM (Resnet 50)	Generation* + Classifier	15.77	24.43	37.22	45.96	51.82

Table 1: Top-1 accuracy on novel classes. *Our methods.

Representation	Lowshot phase	n=1	2	5	10	20
Baseline	Classifier	29.16	33.53	41.57	46.33	49.74
Baseline	Generation* + Classifier	33.60	36.83	42.11	46.70	51.65
SGM*	Classifier	31.83	36.73	44.45	48.79	51.77
SGM*	Generation* + Classifier	34.12	38.09	44.50	48.82	51.79
Batch SGM*	Classifier	31.84	36.78	44.63	49.05	52.11
Triplets	Classifier	28.09	32.16	37.17	39.85	41.47
L2*	Classifier	33.18	38.21	44.07	46.74	48.37
Dropout	Classifier	31.29	36.05	42.12	45.33	47.53
Decov	Classifier	30.13	34.21	43.61	48.65	51.70
L1*	Classifier	30.37	35.40	42.82	46.80	49.39
Multiverse	Classifier	30.19	33.11	40.80	46.67	50.92
Baseline	Model Regression	29.70	33.84	38.15	39.23	40.21
Baseline	Matching Network	30.08	34.78	41.74	45.81	48.81
Baseline-ft	Classifier	28.14	31.55	39.61	45.04	48.63
Baseline (Resnet 50)	Classifier	36.33	42.95	52.71	57.79	61.01
Baseline (Resnet 50)	Generation* + Classifier	40.86	45.65	51.90	56.74	61.03
SGM (Resnet 50)	Classifier	38.73	45.06	53.40	57.90	60.93
SGM (Resnet 50)	Generation* + Classifier	41.05	45.76	53.39	57.90	60.92

Table 2: Top-1 accuracy on all classes. *Our methods.

Representation	Lowshot phase	n=1	2	5	10	20
Baseline	Classifier	0.20	0.42	0.52	0.40	0.21
Baseline	Generation* + Classifier	0.58	0.52	0.32	0.44	0.17
SGM*	Classifier	0.43	0.51	0.32	0.51	0.40
SGM*	Generation* + Classifier	0.40	0.55	0.34	0.37	0.34
Batch SGM*	Classifier	0.62	0.51	0.35	0.38	0.39
Triplets	Classifier	0.58	0.68	0.30	0.60	0.34
L2*	Classifier	0.62	0.57	0.42	0.42	0.28
Dropout	Classifier	0.72	0.47	0.31	0.44	0.32
Decov	Classifier	0.51	0.21	0.30	0.68	0.38
L1*	Classifier	0.18	0.48	0.26	0.58	0.34
Multiverse	Classifier	0.42	0.43	0.29	0.55	0.36
Baseline	Model Regression	0.29	0.43	0.38	0.49	0.17
Baseline	Generation* + Classifier	0.45	0.45	0.25	0.54	0.26
Baseline-ft	Classifier	0.53	0.63	0.17	0.40	0.28
Baseline (Resnet 50)	Classifier	0.49	0.77	0.24	0.41	0.20
Baseline (Resnet 50)	Generation* + Classifier	0.67	0.47	0.19	0.25	0.25
SGM (Resnet 50)	Classifier	0.30	0.54	0.16	0.27	0.28
SGM (Resnet 50)	Generation* + Classifier	0.54	0.25	0.20	0.25	0.30

Table 3: Standard deviation: top-5 accuracy, novel classes. *Our methods.

Representation	Lowshot phase	n=1	2	5	10	20
Baseline	Classifier	0.10	0.28	0.27	0.23	0.06
Baseline	Generation* + Classifier	0.33	0.36	0.23	0.27	0.08
SGM*	Classifier	0.28	0.29	0.18	0.28	0.26
SGM*	Generation* + Classifier	0.24	0.33	0.20	0.23	0.27
Batch SGM*	Classifier	0.35	0.32	0.22	0.25	0.26
Triplets	Classifier	0.36	0.40	0.22	0.37	0.21
L2*	Classifier	0.41	0.37	0.26	0.26	0.18
Dropout	Classifier	0.45	0.34	0.20	0.28	0.17
Decov	Classifier	0.29	0.16	0.20	0.42	0.24
L1*	Classifier	0.11	0.32	0.19	0.35	0.20
Multiverse	Classifier	0.24	0.27	0.15	0.34	0.28
Baseline	Model Regression	0.19	0.30	0.25	0.29	0.14
Baseline	Generation* + Classifier	0.37	0.35	0.23	0.35	0.20
Baseline-ft	Classifier	0.34	0.43	0.14	0.23	0.21
Baseline (Resnet 50)	Classifier	0.30	0.50	0.12	0.25	0.13
Baseline (Resnet 50)	Generation* + Classifier	0.44	0.30	0.12	0.16	0.16
SGM (Resnet 50)	Classifier	0.19	0.32	0.10	0.18	0.16
SGM (Resnet 50)	Generation* + Classifier	0.33	0.17	0.11	0.17	0.18

Table 4: Standard deviation: top-5 accuracy, all classes. *Our methods.

Representation	Lowshot phase	n=1	2	5	10	20
Baseline	Classifier	0.22	0.23	0.55	0.61	0.19
Baseline	Generation* + Classifier	0.21	0.31	0.51	0.43	0.27
SGM*	Classifier	0.28	0.14	0.53	0.40	0.41
SGM*	Generation* + Classifier	0.43	0.36	0.42	0.41	0.47
Batch SGM*	Classifier	0.33	0.40	0.49	0.35	0.47
Triplets	Classifier	0.13	0.37	0.54	0.32	0.38
L2*	Classifier	0.28	0.60	0.48	0.34	0.30
Dropout	Classifier	0.24	0.61	0.84	0.52	0.42
Decov	Classifier	0.09	0.24	0.30	0.38	0.37
L1*	Classifier	0.23	0.46	0.51	0.59	0.25
Multiverse	Classifier	0.17	0.19	0.56	0.59	0.29
Baseline	Model Regression	0.15	0.41	0.52	0.38	0.39
Baseline	Generation* + Classifier	0.52	0.87	0.31	0.30	0.30
Baseline-ft	Classifier	0.23	0.29	0.68	0.35	0.43
Baseline (Resnet 50)	Classifier	0.07	0.62	0.49	0.35	0.23
Baseline (Resnet 50)	Generation* + Classifier	0.26	0.42	0.73	0.43	0.36
SGM (Resnet 50)	Classifier	0.18	0.56	0.43	0.33	0.44
SGM (Resnet 50)	Generation* + Classifier	0.28	0.42	0.38	0.39	0.43

Table 5: Standard deviation: top-1 accuracy, novel classes. *Our methods.

Representation	Lowshot phase	n=1	2	5	10	20
Baseline	Classifier	0.10	0.19	0.26	0.39	0.12
Baseline	Generation* + Classifier	0.12	0.20	0.29	0.29	0.17
SGM*	Classifier	0.17	0.17	0.30	0.26	0.28
SGM*	Generation* + Classifier	0.28	0.22	0.24	0.29	0.33
Batch SGM*	Classifier	0.25	0.30	0.31	0.23	0.24
Triplets	Classifier	0.08	0.28	0.30	0.17	0.22
L2*	Classifier	0.16	0.40	0.28	0.20	0.20
Dropout	Classifier	0.13	0.37	0.49	0.30	0.18
Decov	Classifier	0.08	0.17	0.20	0.27	0.26
L1*	Classifier	0.11	0.31	0.24	0.33	0.13
Multiverse	Classifier	0.09	0.13	0.36	0.36	0.15
Baseline	Model Regression	0.10	0.25	0.32	0.21	0.20
Baseline	Generation* + Classifier	0.43	0.47	0.36	0.30	0.27
Baseline-ft	Classifier	0.11	0.17	0.43	0.19	0.25
Baseline (Resnet 50)	Classifier	0.07	0.38	0.28	0.26	0.18
Baseline (Resnet 50)	Generation* + Classifier	0.14	0.25	0.42	0.26	0.25
SGM (Resnet 50)	Classifier	0.11	0.36	0.29	0.21	0.26
SGM (Resnet 50)	Generation* + Classifier	0.21	0.30	0.24	0.24	0.24

Table 6: Standard deviation: top-1 accuracy, all classes. *Our methods.

4 Other experimental details

Tables 7 and 9 show the base and novel categories we use for cross-validation. Tables 8 and 10 show the base and novel categories we use for our final results.

Figure 2 shows the ResNet-10 architecture. The ResNet-50 architecture is as described in [1].

5 Unpacking the low standard deviation

The standard deviation in these experiments seems fairly low given the fact that we are learning classifiers from only a few examples. We believe that this is because we are averaging the performance over multiple categories. To see if this is indeed the case, we ran an experiment where we chose a single category (picked once, uniformly at random), and ran five different low-shot learning experiments with $n = 2$, that is, with 2 randomly chosen examples from the novel category each time. The top-5 accuracy on the novel category for the baseline was $31.6 \pm 11.6\%$, while that for the SGM representation with generation (with 3 generated examples in total) was $61.6 \pm 7.0\%$. This gives a glimpse into the kind of improvements we see for single categories, and the amount of variance there is for individual categories.

We thank the reviewers for suggesting this experiment.

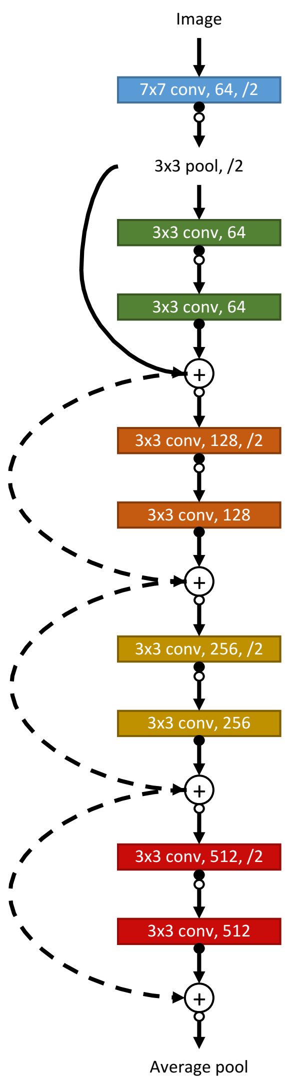

Figure 2: The ResNet-10 architecture. White circles represent ReLU and black circles show batch normalization. Identity shortcuts are shown as solid arrows, while dashed arrows show a 1×1 convolution with stride 2 to match spatial resolution and feature dimension.

n03394916	n02342885	n02782093	n02676566	n03000247	n03062245	n09399592	n02169497
n07615774	n01484850	n01819313	n02102318	n03874293	n02526121	n02835271	n03983396
n07749582	n07584110	n02091244	n04517823	n02749479	n07583066	n01943899	n03344393
n03379051	n03538406	n01698640	n02666196	n03627232	n02486410	n02988304	n03843555
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n02391049	n02111500	n02106662	n01632458	n03481172	n02091134	n04192698	n04116512
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n02951358	n01950731	n02488291	n03085013	n03777754	n03630383	n01873310	n03670208
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n03841143							

Table 7: C^1_{base}

References

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[2] Oriol Vinyals, Charles Blundell, Timothy P. Lillicrap, Koray Kavukcuoglu, and Daan Wierstra. Matching networks for one shot learning. *CoRR*, abs/1606.04080, 2016.

[3] Yu-Xiong Wang and Martial Hebert. Learning to learn: Model regression networks for easy small sample learning. In *ECCV*, 2016.

n01807496	n02916936	n03794056	n01847000	n04044716	n04136333	n11879895	n03534580
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Table 8: C^2_{base}

n10565667	n02978881	n03126707	n07693725	n01818515	n02802426	n03877845	n02094114
n03781244	n03443371	n02256656	n02087394	n02111129	n02074367	n02892767	n03724870
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n02115641	n04204238	n04550184	n03929660	n01843065	n03590841	n04366367	n03793489
n02514041	n02692877	n02123159	n04201297	n02396427	n03764736	n02051845	n01704323
n02641379	n01983481	n03666591	n03832673	n03786901	n02088364	n02097474	n07695742
n03930313	n03902125	n02823428	n02089867	n03982430	n04515003	n03272562	n03623198
n04376876	n01532829	n02971356	n13054560	n07613480	n02101006	n03770679	n02095570
n01855672	n03877472	n01986214	n02028035	n07892512	n02096294	n02422106	n02437312
n07745940	n02701002	n07248320	n02843684	n02165456	n02105855	n01980166	n03461385
n03041632	n03956157	n03476684	n02727426	n04259630	n15075141	n13133613	n04254120
n03662601	n03485407	n07715103	n02119022	n01985128	n03075370	n02457408	n04326547
n02093647	n04562935	n04026417	n04125021	n02174001	n02895154	n04270147	n06359193
n07873807	n04501370	n13052670	n02130308	n02277742	n02123394	n03617480	n01817953
n12998815	n04371430	n02168699	n03482405	n02098413	n07717410	n04367480	n02109961
n04275548	n07871810	n02877765	n04409515	n07831146	n02389026	n03250847	n01734418
n02033041	n02415577	n02808304	n04599235	n03866082	n02259212	n02927161	n04522168
n02397096	n03788365	n01833805	n02115913	n03888605	n01784675	n04479046	n04235860
n13037406	n02909870	n01685808	n03452741	n03445924	n01872401	n04208210	n02814533
n02113624	n01675722	n03933933	n03998194	n03447447	n02113799	n04604644	n02107312
n01580077	n02708093	n03937543	n02112137	n02124075	n02489166	n02125311	n04141975
n02027492	n03970156	n02104365	n02100236	n04486054	n04243546	n02137549	n02443114
n02002556	n04141076	n02100583	n03776460	n02804414	n01860187	n01773549	n03692522
n03347037	n03259280	n02085782	n02655020	n02815834	n04417672	n02093428	n03691459
n02177972	n02791270	n02097047	n03991062	n04069434	n04418357	n04467665	n04111531
n02979186	n04465501	n01751748	n03584829	n02319095	n03404251	n03124043	n04392985
n03141823	n03967562	n03903868	n01558993	n02090721	n02106030	n07711569	n04049303
n06596364	n04317175	n02363005	n04443257	n03759954	n02113978	n02504013	n03220513
n03032252	n03954731	n03000684	n02106550	n04532106	n03733281	n02500267	n02086240
n04023962	n01737021	n02441942	n04462240				

Table 9: C^1_{novel}

n03710193	n02105412	n07753275	n03908714	n03535780	n09468604	n02113023	n01677366
n02536864	n01728920	n02483362	n02128757	n04154565	n04344873	n09256479	n07720875
n03196217	n07875152	n01871265	n01796340	n04265275	n03961711	n01496331	n03272010
n03388043	n02102480	n02837789	n03721384	n03710637	n02097209	n02109047	n02095314
n03717622	n01601694	n02056570	n02480855	n03207941	n04149813	n02233338	n02101556
n03388183	n02058221	n03742115	n04118776	n02879718	n02102177	n03637318	n03179701
n02328150	n04612504	n02099712	n02504458	n03729826	n03042490	n04209133	n04251144
n04356056	n03249569	n04037443	n01644373	n03314780	n02487347	n02699494	n03837869
n03125729	n02950826	n03733131	n03887697	n03942813	n03095699	n02807133	n04228054
n02088632	n02280649	n02114712	n03000134	n02110341	n01824575	n04040759	n07717556
n04523525	n01774750	n03599486	n01682714	n04041544	n07760859	n02279972	n02002724
n01955084	n02007558	n01748264	n03935335	n02096585	n03838899	n02281787	n02086079
n04554684	n04229816	n03649909	n03110669	n04447861	n03804744	n02107683	n02025239
n02094433	n03676483	n01855032	n02037110	n09421951	n02093991	n04328186	n03899768
n02493509	n01768244	n03633091	n02116738	n03657121	n03895866	n01978287	n09193705
n03773504	n03146219	n03445777	n02128925	n07753592	n02128385	n02111889	n04442312
n03325584	n02797295	n02088094	n02092339	n01729322	n04487081	n03598930	n01667778
n02787622	n07718472	n07754684	n03938244	n02219486	n03791053	n06794110	n01917289
n03958227	n03018349	n02113712	n03980874	n03530642	n02483708	n01644900	n02497673
n04461696	n03733805	n03710721	n04458633	n01984695	n04357314	n01689811	n03803284
n03944341	n12620546	n03680355	n02672831	n02110627	n07716358	n04238763	n03891332
n02132136	n02105251	n03133878	n03825788	n01828970	n01877812	n04355933	n03891251
n04380533	n02113186	n02017213	n02013706	n02108089	n02097130	n02963159	n03857828
n02190166	n03459775	n01774384	n02817516	n07836838	n04347754	n03690938	n01744401
n04008634	n01664065	n01631663	n02104029	n07590611	n02108422	n02094258	n01629819
n07714990	n07920052	n03180011	n03255030	n01531178	n03775546	n01843383	n04141327
n01692333	n03207743	n04398044	n03063689	n02101388	n03709823	n07614500	n02110063
n04127249	n02085620	n04263257	n02129165	n02129604	n09288635	n02102973	n02788148
n03424325	n02490219	n02231487	n02106382	n02229544	n01930112	n03642806	n04067472
n02106166	n04536866	n02098286	n01518878	n01440764	n02444819	n02484975	n02093859
n03868242	n03223299	n02869837	n02346627	n03017168	n02906734	n02105162	n02860847
n01498041	n02793495	n02730930	n02088466	n03337140	n01944390	n04311174	n03782006
n04399382	n02172182	n03447721	n09472597	n09332890	n07716906	n03876231	n03028079
n02777292	n02110958	n01514668	n03047690	n02892201	n01775062	n04370456	n03100240
n03063599	n01753488	n01667114	n04133789	n02133161	n02018795	n07684084	n03595614
n02099849	n02098105	n04004767	n02840245	n04355338	n03109150	n02165105	n02325366
n02138441	n03840681	n02093256	n03065424	n02127052	n04592741	n02105505	n04273569
n02494079	n02790996	n02134418	n10148035	n03160309	n02981792	n04009552	n03977966
n03584254	n04371774	n02102040	n04596742	n02111277	n01669191	n03492542	

Table 10: C^2_{novel}