



Learning Structured Representations by Embedding Class Hierarchy

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Hierarchical label structures widely exist in many real-world datasets...

flower aqua mammal fish

root

CIFAR100 Tree

Isshiki 2020; Krizhevsky, 2009



Tabin & Mohammad 2016; Deng et al. 2009

German Shepherd

Golden Retriever







Ragdoll



German Shepherd



Golden Retriever



Ragdoll



Permutation Invariant Representation



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"Distance" in Label Hierarchy

"Distance" in Label Hierarchy

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"Distance" in Label Hierarchy

"Distance" in Label Hierarchy

Cophenetic Correlation Coefficient (CPCC) [Sokal & Rohlf (1962)]

$$CPCC(d_{\mathcal{T}},\rho) := \frac{\sum_{i < j} (d_{\mathcal{T}}(v_i, v_j) - \overline{d_{\mathcal{T}}})(\rho(v_i, v_j) - \overline{\rho})}{\sqrt{\sum_{i < j} (d_{\mathcal{T}}(v_i, v_j) - \overline{d_{\mathcal{T}}})^2}} \sqrt{\sum_{i < j} (\rho(v_i, v_j) - \overline{\rho})^2}}$$

 $\rightarrow
ho(v_i, v_j) :=$ ^{The Euclidean distance between} two class centroids, where vi and vj are classes.</sup>

 $\rightarrow d_{\mathcal{T}}(v_i, v_j) :=$ The shortest distance between two vertices.

With CPCC as a regularizer...

$$\mathcal{L}(\mathcal{D}) = \sum_{(x,y)\in\mathcal{D}} \ell(y, \hat{y}) - \lambda \cdot \operatorname{CPCC}(d_{\mathcal{T}},
ho)$$

With CPCC as a regularizer...

$$\mathcal{L}(\mathcal{D}) = \sum_{(x,y)\in\mathcal{D}} \ell(y,\hat{y}) - \lambda \cdot \operatorname{CPCC}(d_{\mathcal{T}},\rho)$$

CPCC is flexible!

- ✓ Replace $\ell(y, \hat{y})$ with **any** flat/hierarchical loss functions
- ✓ Applicable to trees with **any** height
- ✓ Computationally Efficient

Structure of Learned Representations



Fine classes from the same coarse classes tend to be closer, and coarse classes tend to be further apart.



Why Structured Representation?

Better Generalization

... to unseen classes and levels

Dataset	Objective	CPCC	Silhouette	FineAcc	MidAcc	CoarseAcc	CoarserAcc
MNIST	Flat	10.80 (1.49)	13.97 (0.72)	99.05 (0.23)	99.38 (0.04)	99.49 (0.08)	N/A
	FlatCPCC	99.96 (0.01)	61.33 (0.42)	99.28 (0.08)	99.38 (0.03)	99.61 (0.03)	N/A
CIFAR100	Flat	24.38 (0.57)	5.59 (0.02)	76.82 (0.30)	80.27 (0.35)	85.59 (0.35)	86.85 (0.27)
	FlatCPCC	84.20 (0.39)	34.40 (0.11)	77.47 (0.27)	81.30 (0.14)	86.95 (0.17)	88.17 (0.17)
	MTL	39.75 (0.33)	8.09 (0.08)	76.56 (0.20)	80.17 (0.22)	85.79 (0.20)	87.11 (0.14)
	MTLCPCC	84.88 (0.58)	31.58 (0.23)	76.90 (0.32)	80.91 (0.29)	87.11 (0.19)	88.39 (0.19)
	Curr	23.81 (0.60)	5.25 (0.11)	76.84 (0.20)	80.40 (0.17)	85.72 (0.16)	87.02 (0.18)
	CurrCPCC	85.32 (0.51)	34.08 (0.23)	77.48 (0.44)	81.42 (0.32)	87.15 (0.19)	88.44 (0.20)
	SumLoss	29.85 (0.63)	4.93 (0.07)	76.78 (0.20)	80.47 (0.22)	85.88 (0.25)	87.11 (0.26)
	SumLossCPCC	84.78 (0.64)	31.16 (0.13)	77.26 (0.12)	81.17 (0.18)	86.99 (0.07)	88.26 (0.02)
	HXE	25.40 (0.68)	8.31 (0.05)	76.58 (0.27)	80.17 (0.24)	85.67 (0.15)	87.02 (0.16)
	HXECPCC	85.13 (0.22)	35.84 (0.18)	76.57 (0.33)	80.63 (0.24)	86.48 (0.20)	87.77 (0.20)
	Soft	55.95 (0.67)	14.48 (0.11)	76.82 (0.06)	80.41 (0.07)	85.84 (0.16)	87.16 (0.07)
	SoftCPCC	85.23 (0.24)	35.80 (0.16)	77.11 (0.16)	81.02 (0.13)	86.63 (0.17)	87.93 (0.14)
	Quad	25.08 (0.26)	6.75 (0.06)	76.40 (0.28)	80.05 (0.27)	85.30 (0.11)	86.67 (0.14)
	QuadCPCC	84.65 (0.32)	34.79 (0.23)	77.10 (0.16)	80.92 (0.12)	86.78 (0.09)	88.04 (0.09)



OOD Detection

Takeaway

- ✓ CPCC successfully creates a structured representation
- ✓ CPCC is flexible and lightweight
- ✓ CPCC leads to better generalization in some scenarios, and can be applied to even more settings (subpopulation shift, OOD detection, ...)

Paper: https://openreview.net/forum?id=7J-30ilaUZM

Code: https://github.com/hanzhaoml/HierarchyCPCC

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Thanks for listening!