HyperPG: Probabilistic Prototypes on Hyperspheres for Interpretable Deep Learning

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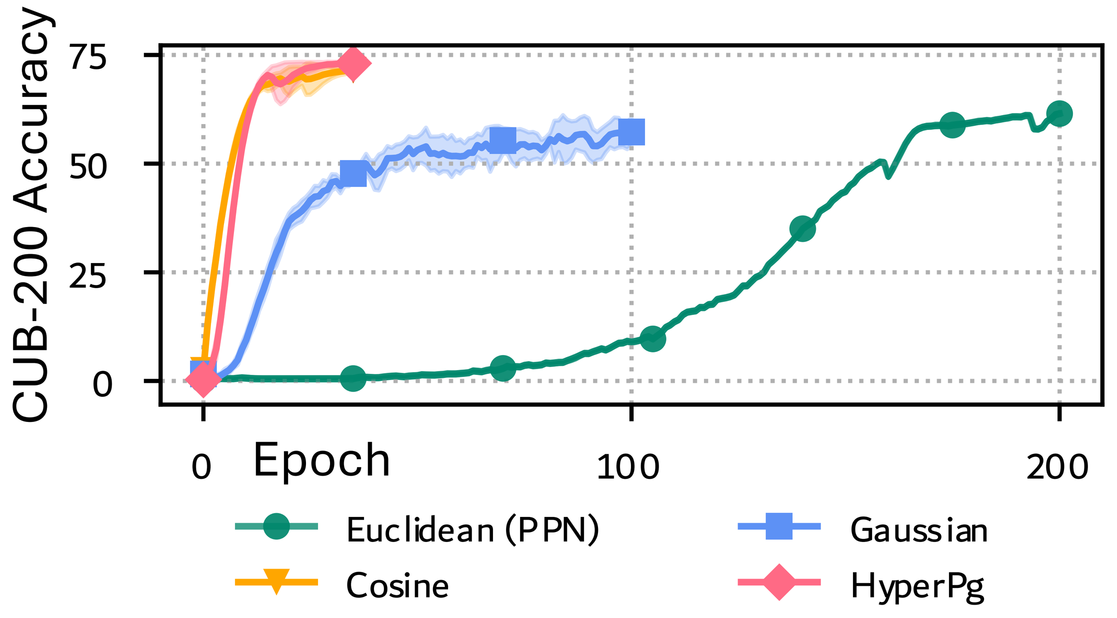
Differences of **Interpretable Prototype Formulations**

- Same Architectures and Training, Different Results
- Only Difference in **Prototype Formulation**

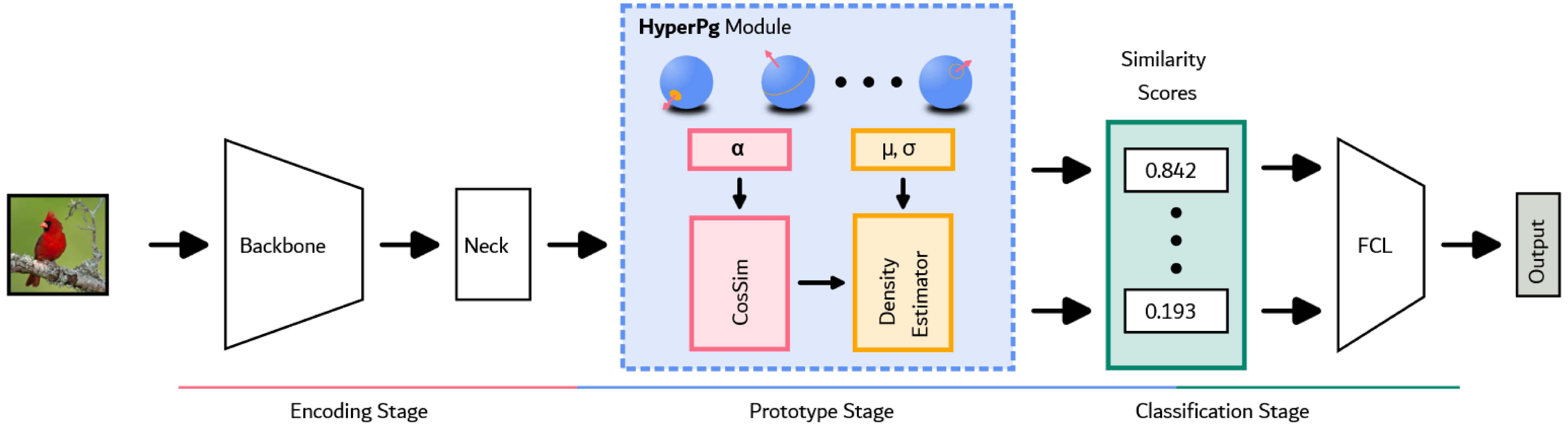
Improved Convergence and Accuracy



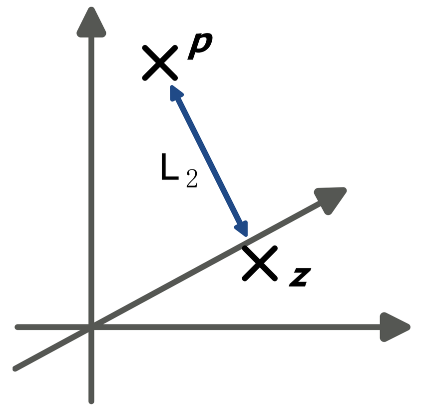
- Simplified Training without warmup

HyperPG combines **Cosine** and **Probabilistic** approach

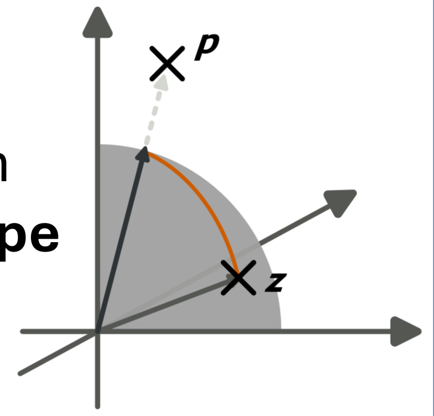
- Learnable **Direction, Mean and Variance**
- Prototypes have **variable focus**
- Compatible with Attention-based Backbones



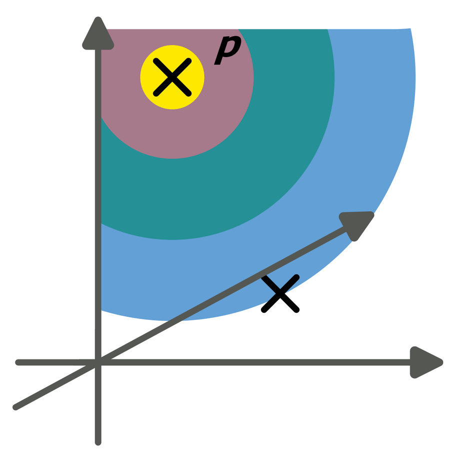
Point Based Prototypes



Compute Euclidean or Cosine **Similarity** between each **Sample and Prototype**



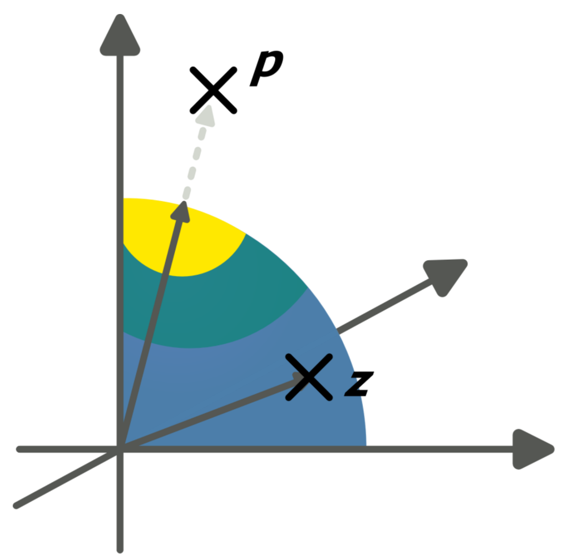
Gaussian Prototypes



Each prototype defines a **Gaussian Distribution.**

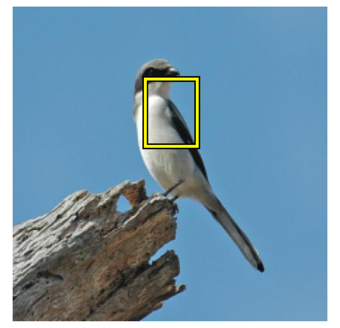
Prototypes learn **different Variance,** i.e. different specificity.

HyperPG Prototypes

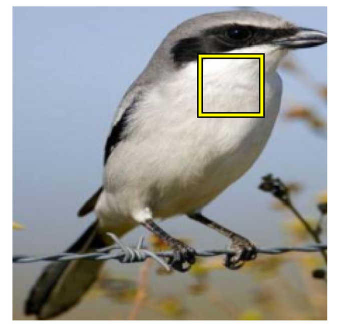


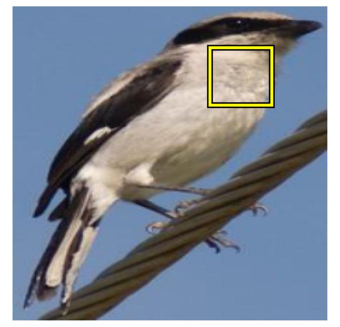
- Combines **Cosine** and **Gaussian Prototypes**
- Cosine Similarity between **Prototype Anchor** and Sample.
- Models **Gaussian Distribution over Cosine Similarities**

Same Interpretability as other Prototypes

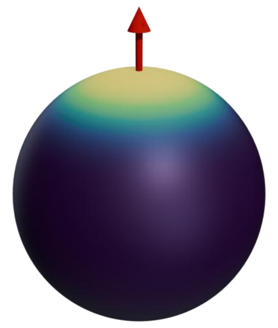


Looks like



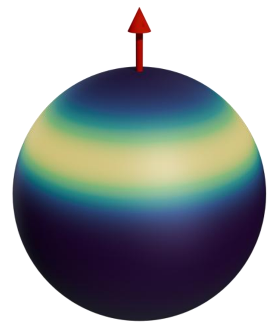


HyperPG: Learnable Mean

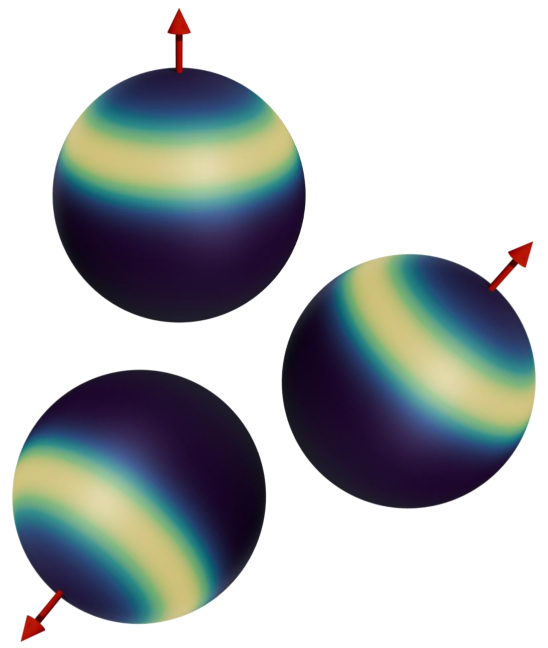


- Similar to **von-Mises-Fisher** Distribution.
- Special Case of **HyperPG Mean=1.0**

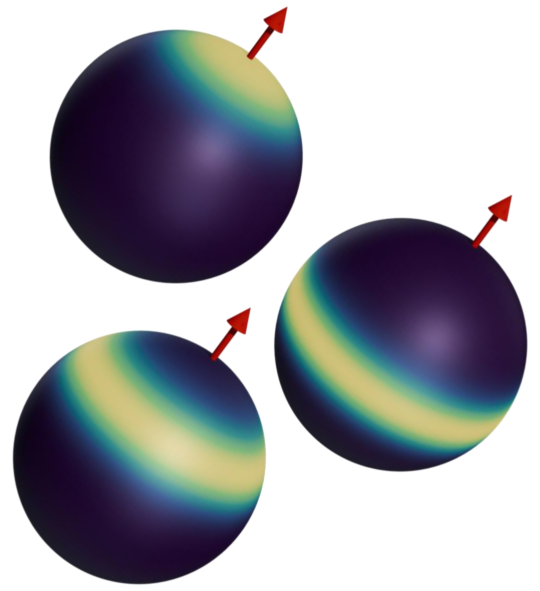
- HyperPG can freely learn mean cosine similarity for each prototype
- **Shifts** main probability mass **away from anchor**



Same Mean
Different Anchor



Different Mean
Same Anchor



Code available on Github:

https://github.com/LiXiling/prob-proto