SAFEAI- 2022

IS IT ALL A CLUSTER GAME? - EXPLORING OUT-OF-DISTRIBUTION DETECTION BASED ON CLUSTERING IN THE EMBEDDING SPACE

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MOTIVATION

- Exploring Out-of-Distribution (OOD) detection problem
  - Embeddings of similar semantic data should cluster together in embedding space
  - Can we learn to distinguish In-Distribution (ID) from OOD samples based on clusters ?

KEY IDEAS

- Using Contrastive Learning (CL) methods
  - cluster similar instances/ classes together
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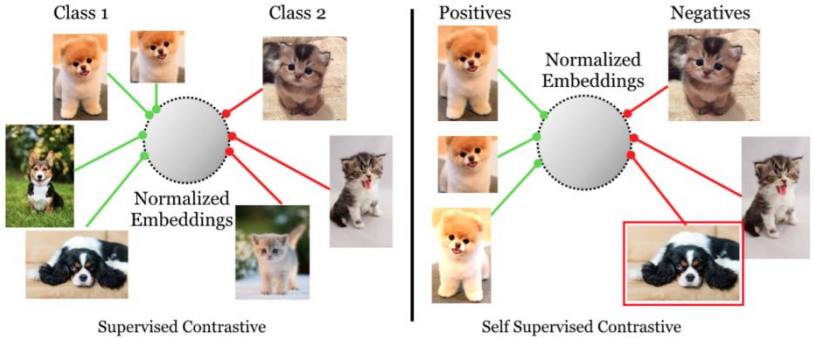

Source: Khosla et. Al:"Supervised Contrastive Learning"

- CL methods used in this work:
  - Supervised Contrastive Learning (**SupCon**)
  - Self-supervised Contrastive Learning (**SimCLR**)

- Baseline:
  - Cross-Entropy (**CE**)

KEY IDEAS/ CONTRIBUTIONS

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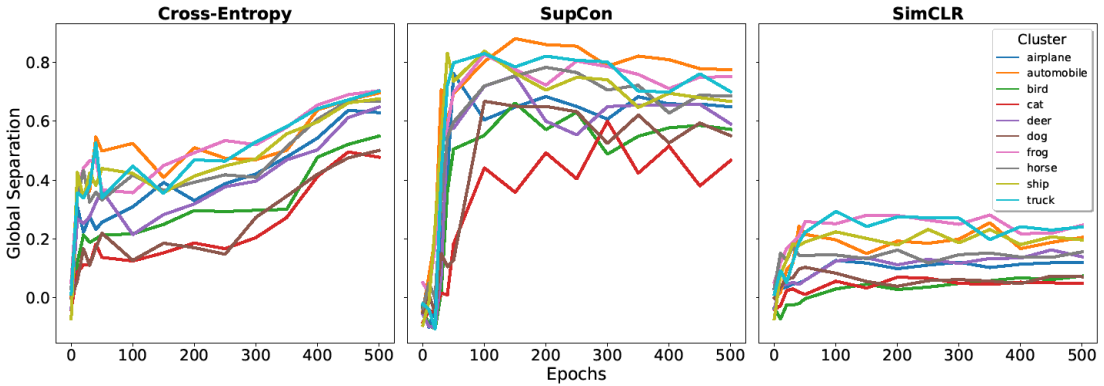
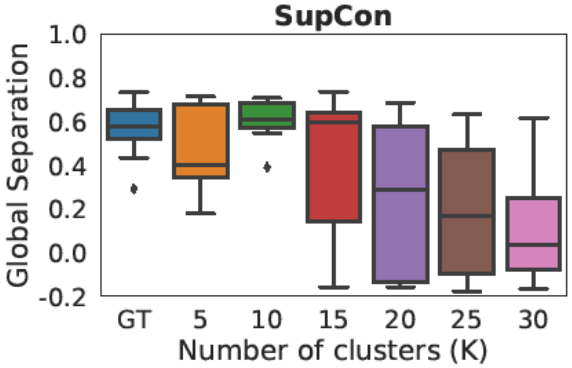
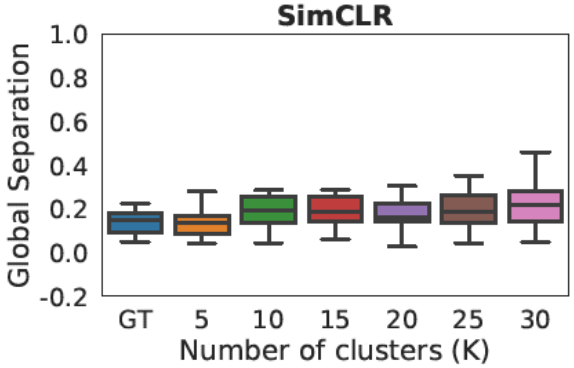


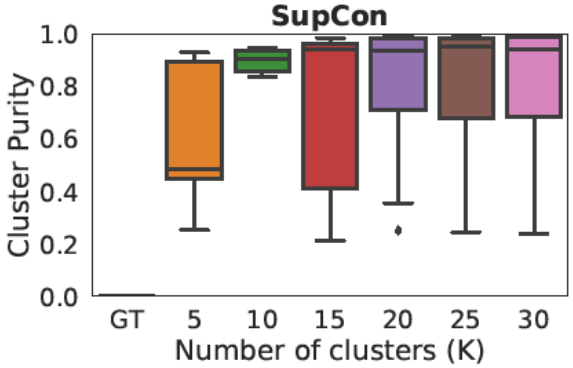
Evolution of cluster separation over time for supervised and self-supervised methods

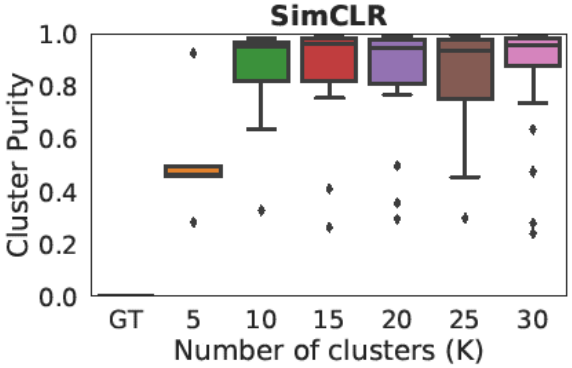
RESULTS: DETERMINING CLUSTER QUALITY

— Comparison of cluster quality for SupCon and SimCLR based on Global Separation and Cluster Purity for GT classes as well as K-means based cluster









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  - Metrics: Mahalanobis and Cosine Similarity
  - AUROC as OOD evaluation scores
  - Cluster-based (K-means/GMM) and Global scores

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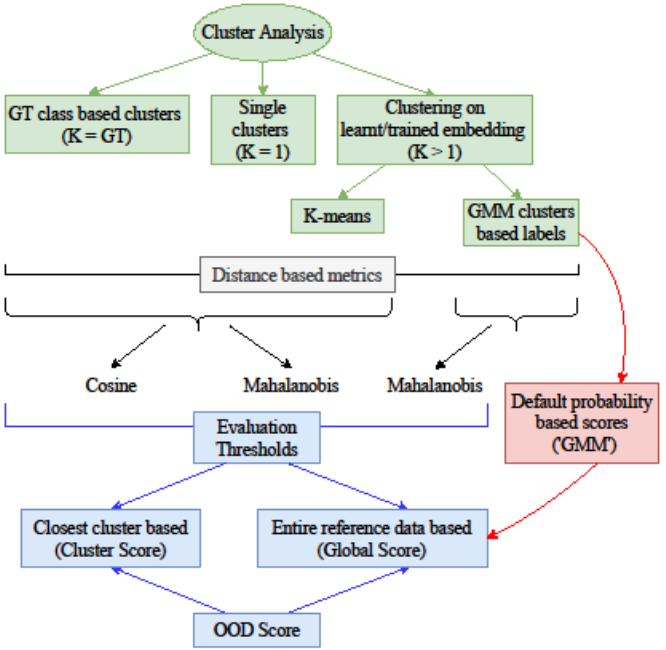
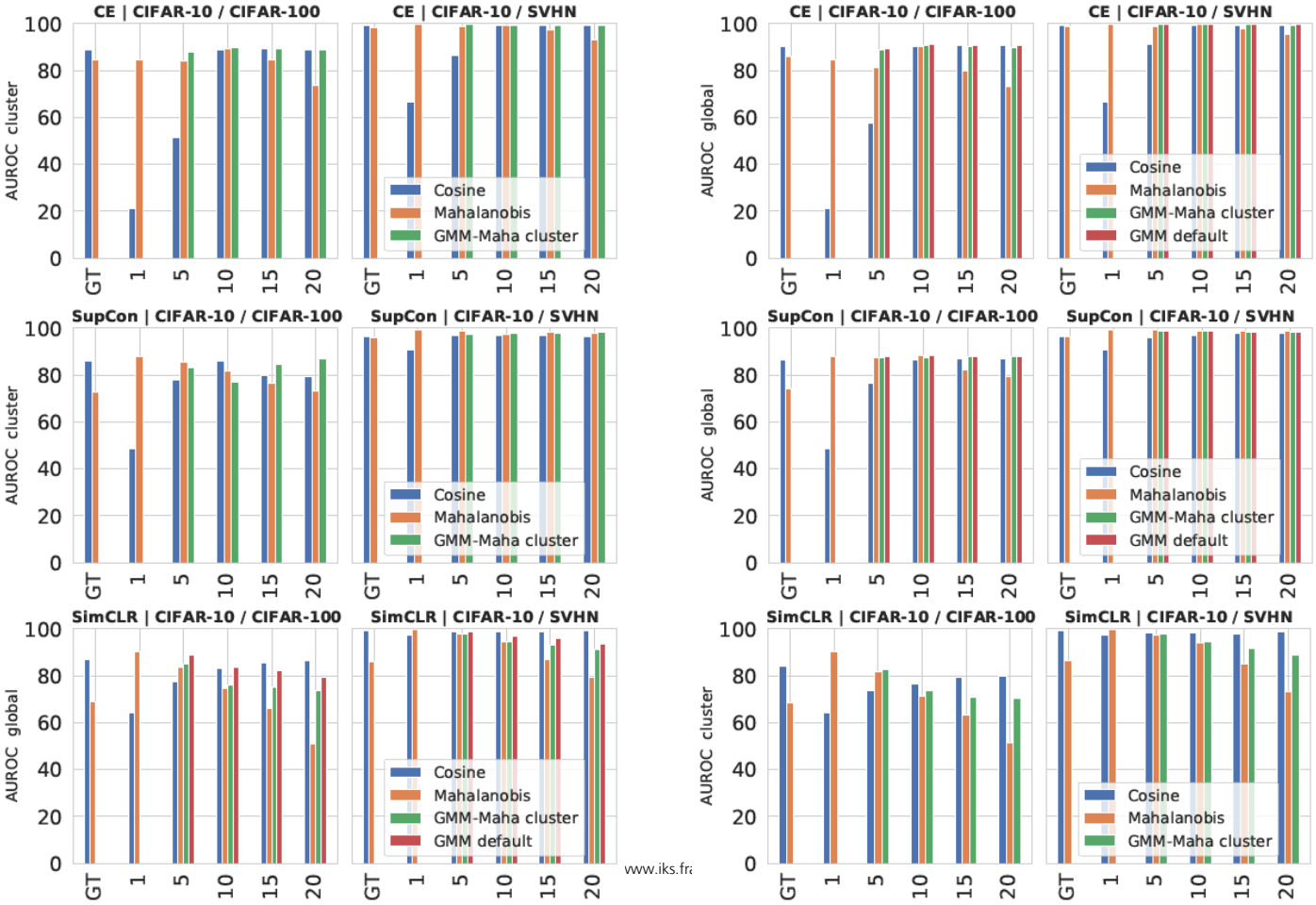


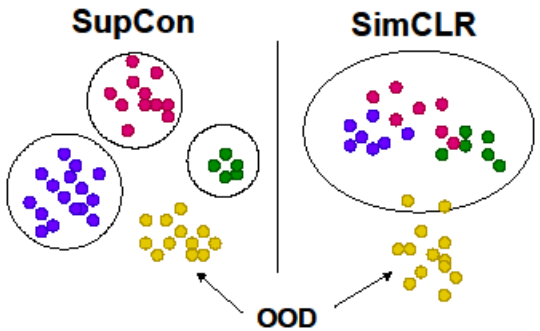
Schematic of our OOD evaluation pipeline

RESULTS: OOD DETECTION



CONCLUSION AND FUTURE WORK

— Depending on supervised or self-supervised training distinct or overlapping clusters of embeddings exist

— Simple less expensive methods like CE provide competitive results

— Across all the different trends investigated, there's no clear winner yet and needs to be further explored