**Overview: Comparison of results.**

This report summarizes the comparison of Grad‑CAM and LIME explanations across our 10‑image dataset as performed in task 2 and task3.

**1. Qualitative Comparison**

* **Spatial Smoothness vs. Sparsity**
  + **Grad‑CAM** produces smooth, somewhat circular blobs sort of heat maps to highlight contiguous regions of high importance. It often covers the entire object silhouette (e.g., the full body of the **American Coot** or the **Tiger Shark**), but can also spill into background areas (e.g., water reflections in the case of American Coot).
  + **LIME** yields a sparse set of superpixels with explicit positive and negative weights. Its maps are “patchy” but highly localized—pinpointing exact segments (e.g., flower clusters in the **Kite** image) and clearly indicating background regions that detract from a class (negative weights over empty water in the shark image).
* **Object‑centric Focus**
  + Grad‑CAM sometimes incorporates contextual cues (e.g., foliage behind a **Vulture**), whereas LIME’s superpixel segmentation ensures activations fall strictly on delineated patches, making it less likely to highlight irrelevant context.
  + In misclassified cases (e.g., **Kite → Spoonbill**), Grad‑CAM highlighted both flowers and sky broadly, while LIME zeroed in on only the pink petals as the (incorrect) positive drivers. This can also be considered as a good explanation for the misclassification.
* **Continuity vs. Fidelity**
  + Grad‑CAM’s continuous regions benefit quick visual interpretation of “where” the model looks, but lack clear signs of what it “rejects.”
  + LIME also includes the negative‑weight patches and provides a fuller picture of the local decision boundary, at the cost of some visual fragmentation.

**2. IoU**

|  |  |
| --- | --- |
| Method | Mean IoU w/ Ground‑Truth Mask |
| Grad‑CAM | 0.287 |
| LIME | 0.305 |

* **Interpretation:** LIME performs better than Grad‑CAM by ~0.02 in terms of IoU, reflecting its tighter adherence to object boundaries. Grad‑CAM’s smoother, more diffuse maps occasionally lower its overlap score, especially on images with fine details (e.g., **Goldfish** with thin fins).

**3. Summary of Trade‑Offs**

* **Grad‑CAM**: Fast to compute (<0.1 s/image), smooth overviews, easy to spot general regions. However, it can over‑highlight context, like inclusion of background details leading to weaker boundary alignment (lower IoU) and it also has no explicit negative cues for the explanations.
* **LIME**: It has higher boundary fidelity (higher IoU), explicit positive/negative contributions, and sharper localization. However, it is slower (~1.9 s/image), can lead to patchy appearance of the mask (as in the common Iguana case) as it is dependent on superpixel granularity.

**Conclusion**  
Grad‑CAM and LIME serve complementary roles: use Grad‑CAM for rapid, broad‐stroke inspection of model attention, and LIME when precise, segment‑level attribution (including what the model suppresses) is required. Their combined insights help both debug misclassifications and build trust in model behavior.