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# Multi-modal proxy learning towards personalized visual multiple clustering

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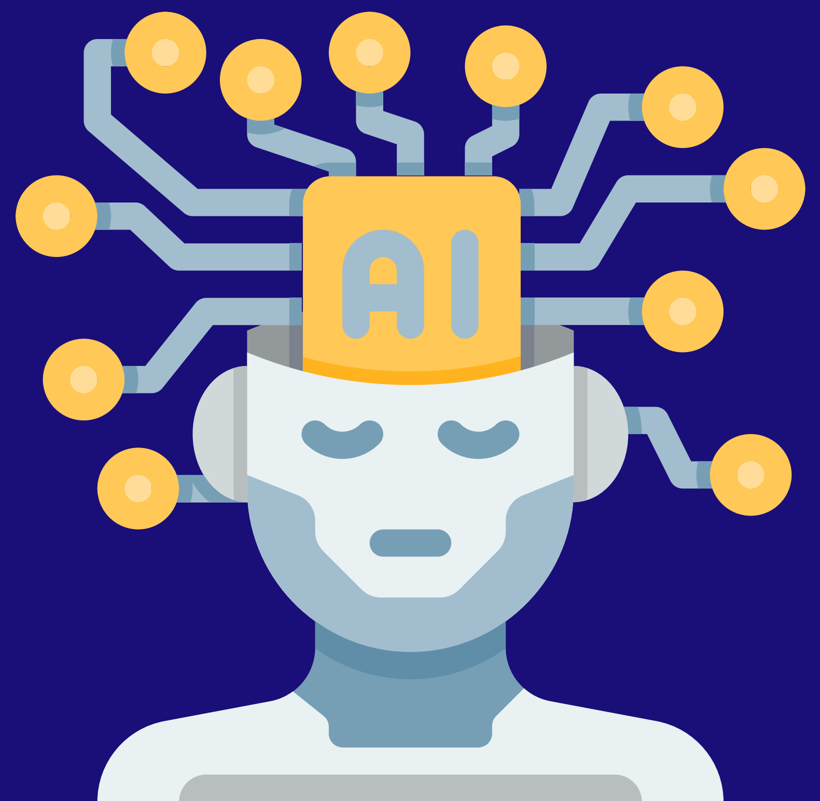


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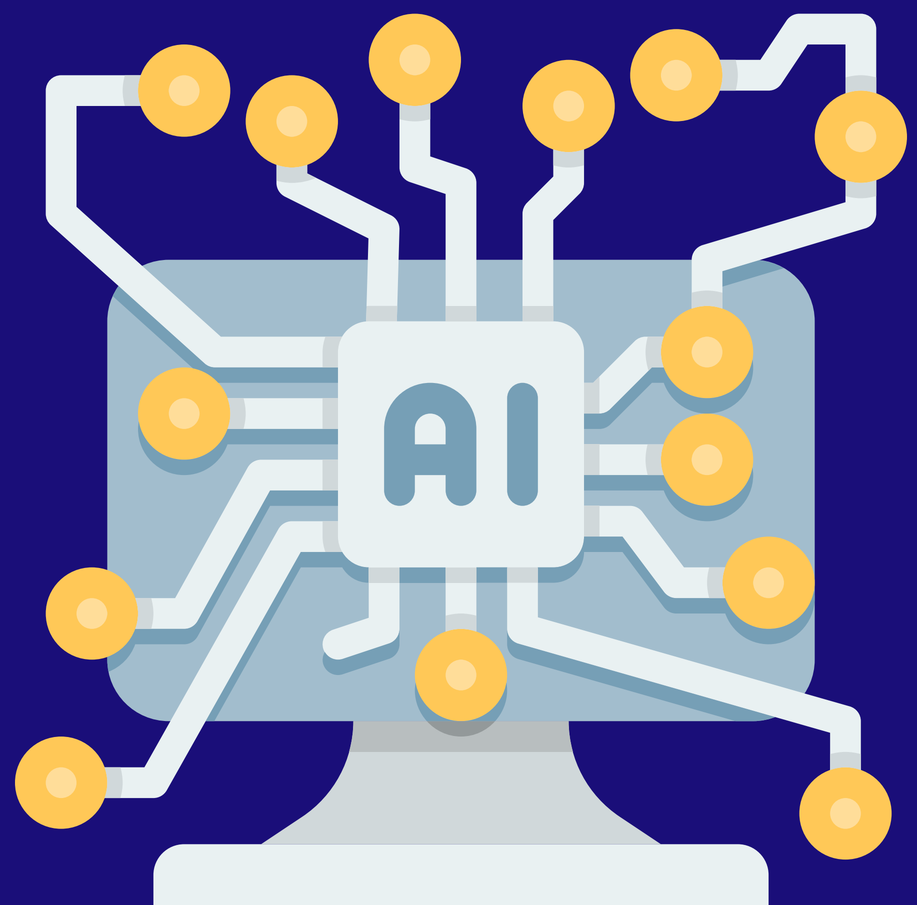
**IIC3666**

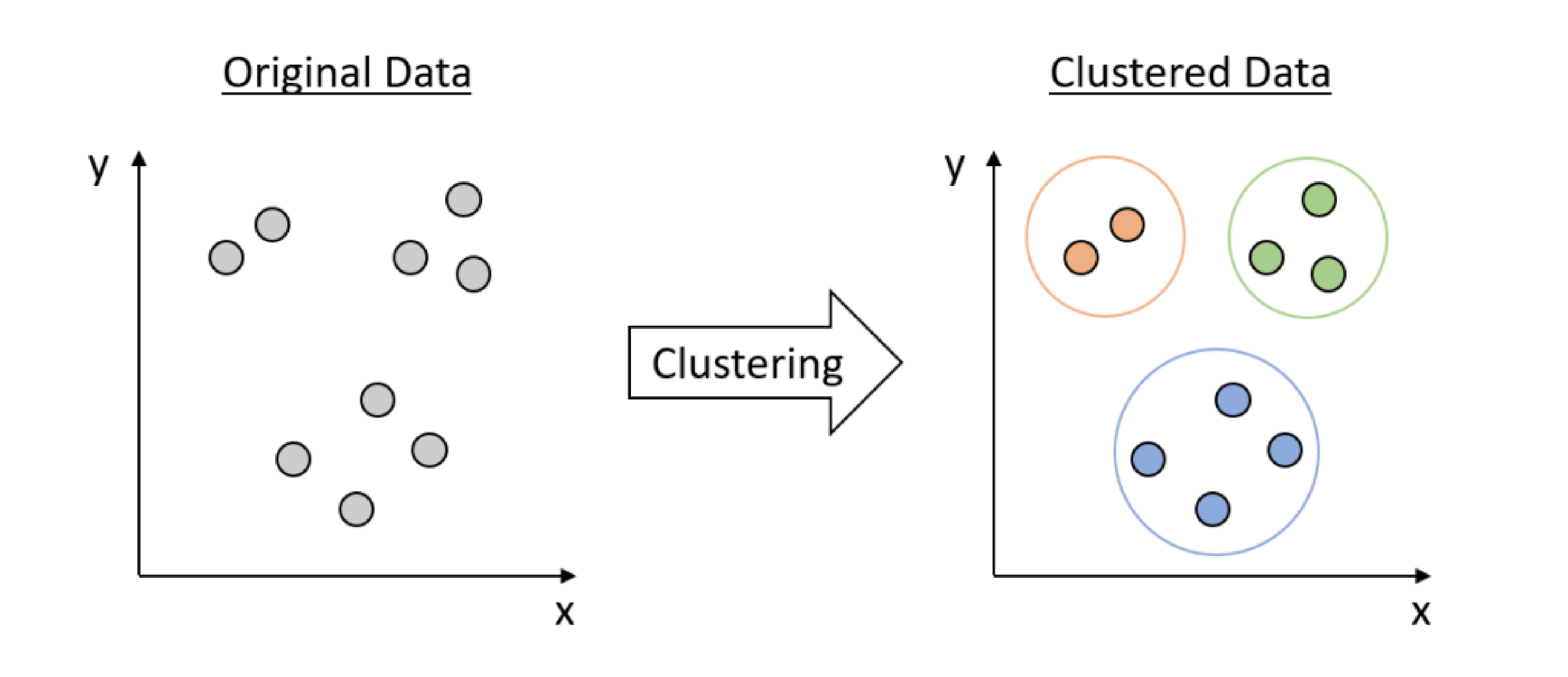
# Índice

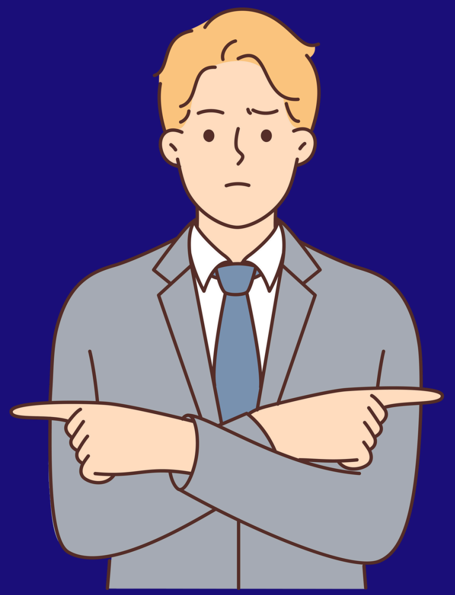




# Contexto

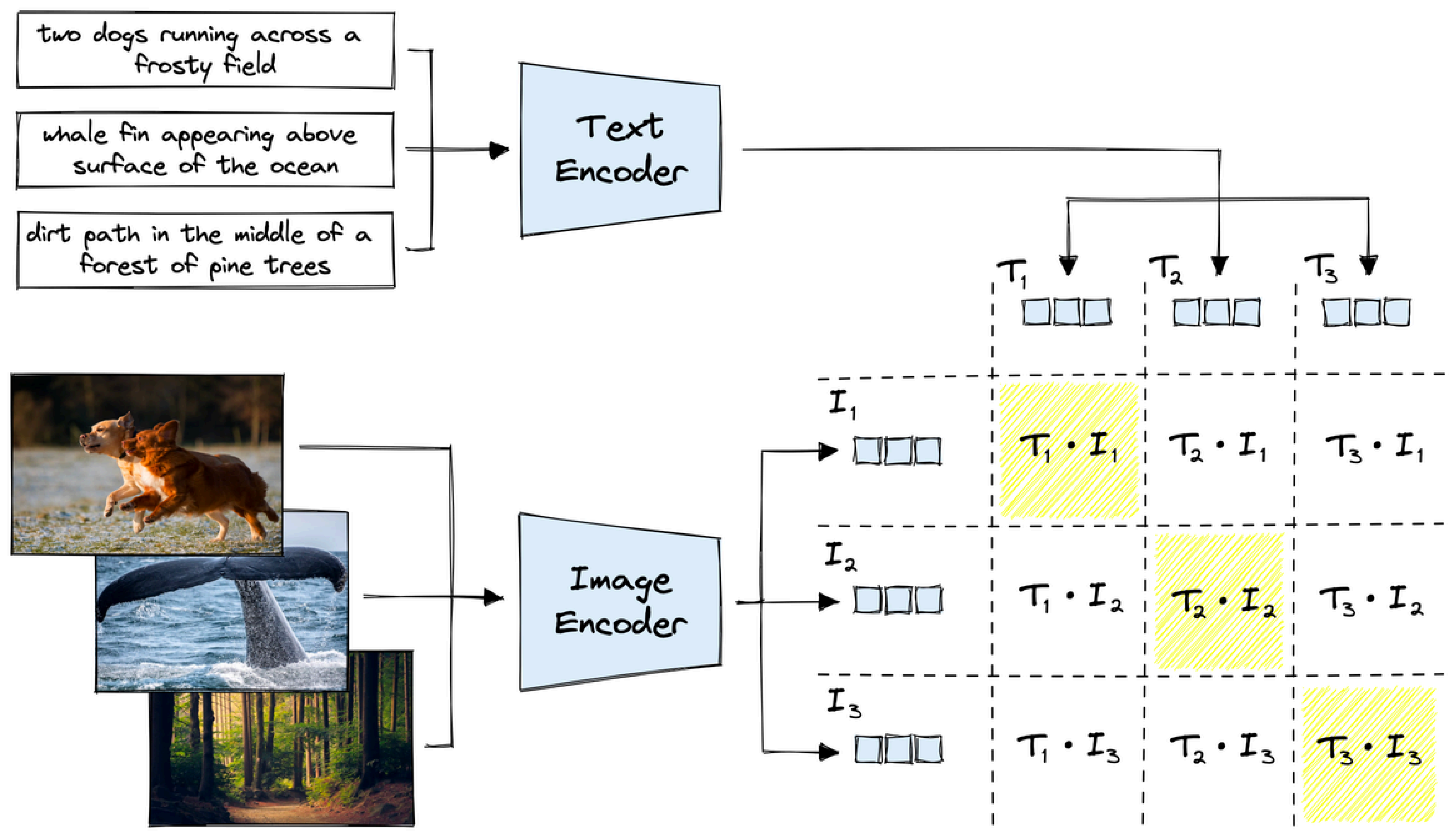
- **Clustering:** Técnica de agrupamiento de datos según similitud
- **Multiple Clustering**: Generar **múltiples agrupaciones** posibles para el mismo conjunto de datos.
- La llegada de **Deep Learning** ayuda en gran medida al **rendimiento** del clustering.
- El **problema**: ¿Cuáles **agrupaciones** son **relevantes**?



# Problema de recomendación

- Enfoque de aprendizaje automático del interés del usuario y agrupación adecuada.
- Multi-Map (Multi-Modal Proxy Learning): Combinación modelos multimodales (CLIP) y modelos de lenguaje (GPT-4).

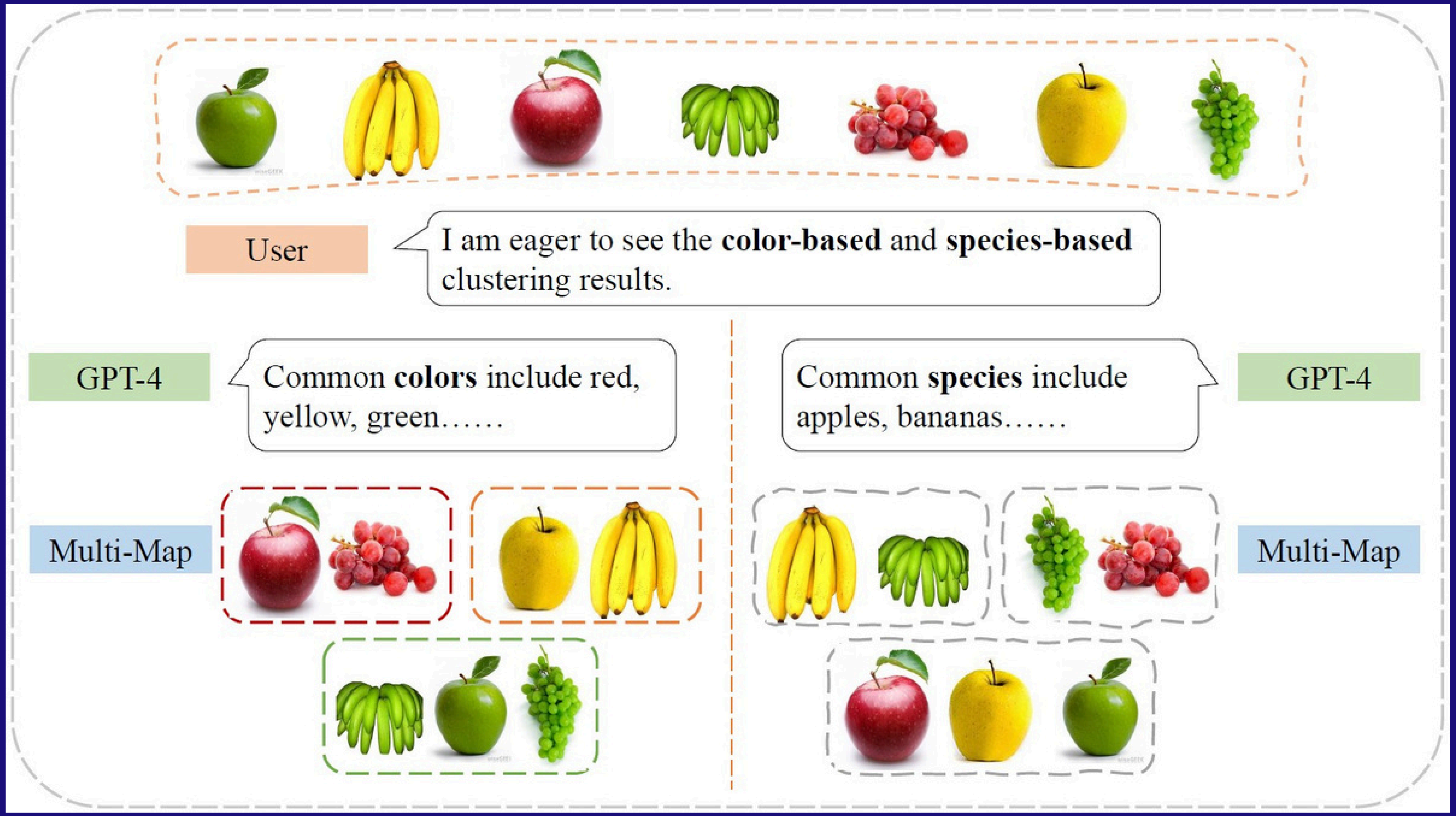



OpenAI

GPT - 4

# Contribución

- Clustering múltiple **Personalizado** y **NO Supervisado**
- Basado en **preferencias del usuario** en **lenguaje natura**l
- **SIN** necesidad de **etiquetas explícitas**.
- **Evita** la **revisión manual** de múltiples clusterings



# Estado del arte y marco teórico


**MSC**

**Algoritmo clásico con hand-crafted features**
Genera múltiples clusterings sin asegurar diversidad

**2017**

**2020**

**ENRC**

**Usa un autoencoder para aprender las features**
Penaliza redundancia en clustering

**CLIP**

**Modelo multimodal**
Backbone visual-textual de Multi MaP, usándolo como encoder

**2021**

**2022**

**CoOp**

**Aprenden prompts óptimos en CLIP**
Inspiración para el aprendizaje de proxies textuales

**AugDMC**

**Aplica data augmentation sobre las imágenes**
Estado del arte de deep multiple clustering

**2023**

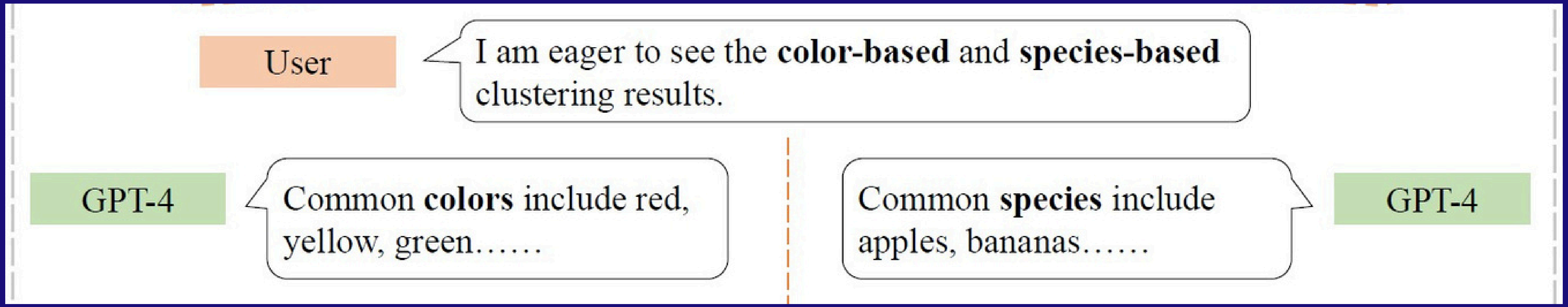
Multiple Clustering

Componentes clave

# Solución

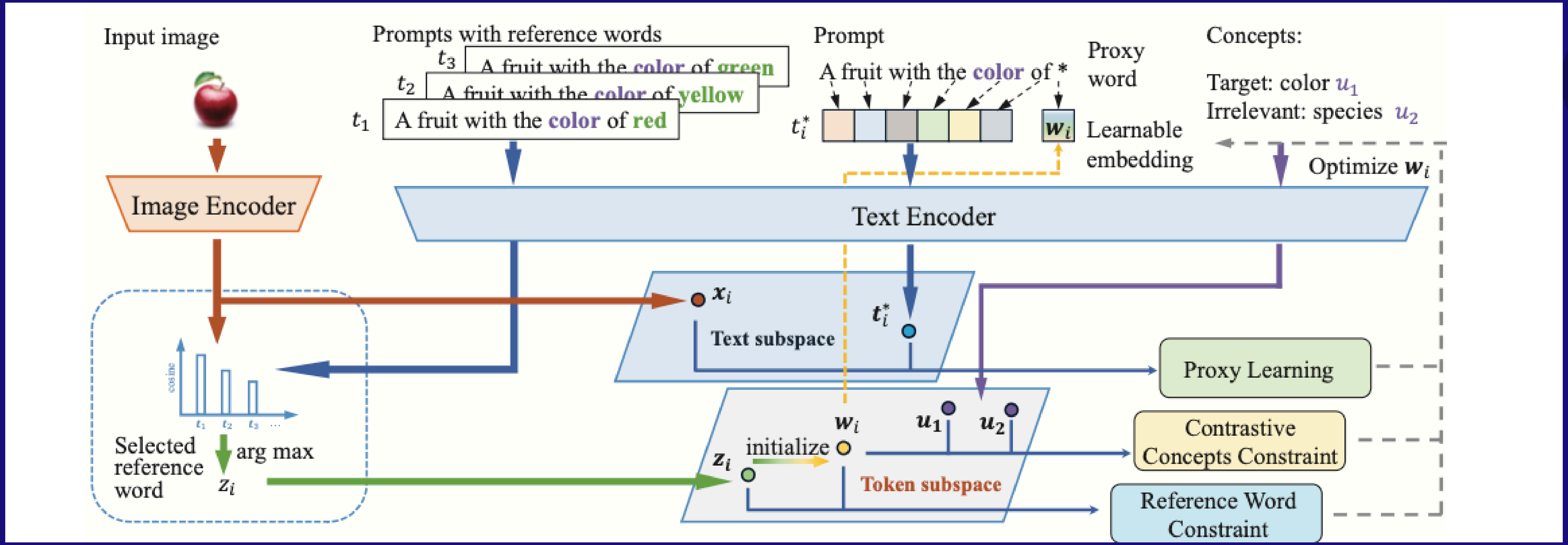
## Flujo de Multi-Map

1. El usuario proporciona un concepto general (ej: "color", "especie").
2. El modelo GPT-4 genera automáticamente palabras concretas relacionadas (ej: "rojo", "verde", etc.).
3. Se codifican esas palabras generando múltiples prompts textuales. Para cada imagen, se selecciona el prompt más adecuado según similitud.



# Solución

## Flujo de Multi-Map




4. Se inicializa un proxy word (vector representativo) con la palabra seleccionada y se optimiza:
    - Para maximizar la similitud con la representación visual de la imagen.
    - Para mantener proximidad al prompt específico y al concepto general proporcionado.
    - Para minimizar confusión entre diferentes conceptos (restricción contrastiva).
5. Finalmente, se ejecuta k-means sobre estos vectores aprendidos, generando agrupaciones personalizadas según interés del usuario.

# Solución

## Pérdidas y Ecuaciones Clave

$$\mathcal{L}\left(\mathbf{w}_i\right) = \mathcal{L}_{\text{align}} + \alpha\mathcal{L}_{\text{reference}} + \beta\mathcal{L}_{\text{concept}}$$

$$\mathcal{L}_{\text{align}} = -\langle f(x_i), h(t_i^*)\rangle$$

$$\mathcal{L}_{\text{reference}} = \|\mathbf{w}_i - \mathbf{z}_i\|_2^2$$

$$\mathcal{L}_{\text{concept}} = -\log \frac{\exp(\mathbf{w}_i^\top \mathbf{u}_w)}{\sum_j \exp(\mathbf{w}_i^\top \mathbf{u}_j)}$$

$x_i$ : Imagen ej: red apple

$t_i^*$ : Prompt para CLIP
ej: "a fruit with the color of red"

$\mathbf{w}_i$ : Proxy Imagen
init como "red", cambia al aprender

$\mathbf{z}_i$ : Palabra referencia
ej: "red"

$\mathbf{u}_w$ : Concepto general
ej: "color"

$\{\mathbf{u}_j\}$ : Otros conceptos
ej. "species", "shape"

# Solución

## Experimentación

- CLIP y GPT-4 no se fine-tunean: sólo **entrenamos** los $\mathbf{w}_i$
- Optimización con **Adam**, momentum = 0.9, durante 1000 epochs.
- Tasa de aprendizaje (**Learning Rate**) seleccionada entre (0.1 a 0.0005).
- Decaimiento de peso (**Weight decay**) seleccionado entre (0.0005 a 0).
- Parámetros de restricciones: **α y β** en rango (0.0 a 1.0). Se escogen por grid-search validando la pérdida total en el conjunto de entrenamiento
- Evaluación usando métricas: Normalized Mutual Information (**NMI**) y Rand Index (**RI**). Miden qué tanta "información" comparten dos particiones; y la proporción de pares de puntos que están de acuerdo en las dos particiones, respectivamente

# Resultados

## Multi-MAP vs Métodos existentes

| Dataset | Clustering | MSC NMI | MSC RI | MCV NMI | MCV RI | ENRC NMI | ENRC RI | iMClusts NMI | iMClusts RI | AugDMC NMI | AugDMC RI | Multi-MaP NMI | Multi-MaP RI |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| ALOI | Color | 0.1563 | 0.3428 | 0.6982 | 0.7439 | 0.9833 | 0.9892 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | Shape | 0.2968 | 0.5199 | 0.7359 | 0.8261 | 0.9732 | 0.9861 | 0.9963 | 0.9989 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Fruit | Color | 0.6886 | 0.8051 | 0.6266 | 0.7685 | 0.7103 | 0.8511 | 0.7351 | 0.8632 | 0.8517 | 0.9108 | **0.8619** | **0.9526** |
| | Species | 0.1627 | 0.6045 | 0.2733 | 0.6597 | 0.3187 | 0.6536 | 0.3029 | 0.6743 | 0.3546 | 0.7399 | **1.0000** | **1.0000** |
| Fruit360 | Color | 0.2544 | 0.6054 | 0.3776 | 0.6791 | 0.4264 | 0.6868 | 0.4097 | 0.6841 | 0.4594 | 0.7392 | **0.6239** | **0.8243** |
| | Species | 0.2184 | 0.5805 | 0.2985 | 0.6176 | 0.4142 | 0.6984 | 0.3861 | 0.6732 | 0.5139 | 0.7430 | **0.5284** | **0.7582** |
| Card | Order | 0.0807 | 0.7805 | 0.0792 | 0.7128 | 0.1225 | 0.7313 | 0.1144 | 0.7658 | 0.1440 | 0.8267 | **0.3653** | **0.8587** |
| | Suits | 0.0497 | 0.3587 | 0.0430 | 0.3638 | 0.0676 | 0.3801 | 0.0716 | 0.3715 | 0.0873 | 0.4228 | **0.2734** | **0.7039** |
| CMUface | Emotion | 0.1284 | 0.6736 | 0.1433 | 0.5268 | 0.1592 | 0.6630 | 0.0422 | 0.5932 | 0.0161 | 0.5367 | **0.1786** | **0.7105** |
| | Glass | 0.1420 | 0.5745 | 0.1201 | 0.4905 | 0.1493 | 0.6209 | 0.1929 | 0.5627 | 0.1039 | 0.5361 | **0.3402** | **0.7068** |
| | Identity | 0.3892 | 0.7326 | 0.4637 | 0.6247 | 0.5607 | 0.7635 | 0.5109 | 0.8260 | 0.5875 | 0.8334 | **0.6625** | **0.9496** |
| | Pose | 0.3687 | 0.6322 | 0.3254 | 0.6028 | 0.2290 | 0.5029 | 0.4437 | 0.6114 | 0.1320 | 0.5517 | **0.4693** | **0.6624** |
| Stanford Cars | Color | 0.2331 | 0.6158 | 0.2103 | 0.5802 | 0.2465 | 0.6779 | 0.2336 | 0.6552 | 0.2736 | 0.7525 | **0.7360** | **0.9193** |
| | Type | 0.1325 | 0.5336 | 0.1650 | 0.5634 | 0.2063 | 0.6217 | 0.1963 | 0.5643 | 0.2364 | 0.7356 | **0.6355** | **0.8399** |
| Flowers | Color | 0.2561 | 0.5965 | 0.2938 | 0.5860 | 0.3329 | 0.6214 | 0.3169 | 0.6127 | 0.3556 | 0.6931 | **0.6426** | **0.7984** |
| | Species | 0.1326 | 0.5273 | 0.1561 | 0.6065 | 0.1894 | 0.6195 | 0.1887 | 0.6077 | 0.1996 | 0.6227 | **0.6013** | **0.8103** |

Table 2. Quantitative comparison. The significantly best results with 95% confidence are in bold.

# Resultados

## Multi-MAP vs Métodos existentes

| Dataset | Clustering | CLIP$_{GPT}$ NMI | CLIP$_{GPT}$ RI | CLIP$_{label}$ NMI | CLIP$_{label}$ RI | Multi-MaP NMI | Multi-MaP RI |
|---|---|---|---|---|---|---|---|
| ALOI | Color | 0.8581 | 0.9407 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | Shape | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Fruit | Color | 0.7912 | 0.9075 | **0.8629** | **0.9780** | 0.8619 | 0.9526 |
| | Species | 0.9793 | 0.9919 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Fruit360 | Color | 0.5613 | 0.7305 | 0.5746 | 0.7673 | **0.6239** | **0.8243** |
| | Species | 0.4370 | 0.7552 | **0.5364** | **0.7631** | 0.5284 | 0.7582 |
| Card | Order | 0.3518 | 0.8458 | 0.3518 | 0.8458 | **0.3653** | **0.8587** |
| | Suits | 0.2711 | 0.6123 | 0.2711 | 0.6123 | **0.2734** | **0.7039** |
| CMUface | Emotion | 0.1576 | 0.6532 | 0.1590 | 0.6619 | **0.1786** | **0.7105** |
| | Glass | 0.2905 | 0.6869 | **0.4686** | **0.7505** | 0.3402 | 0.7068 |
| | Identity | 0.1998 | 0.6388 | 0.2677 | 0.7545 | **0.6625** | **0.9496** |
| | Pose | 0.4088 | 0.6473 | 0.4691 | 0.6409 | **0.4693** | **0.6624** |
| Stanford Cars | Color | 0.6539 | 0.8237 | 0.6830 | 0.8642 | **0.7360** | **0.9193** |
| | Type | 0.6207 | 0.7931 | **0.6429** | **0.8456** | 0.6355 | 0.8399 |
| Flowers | Color | 0.5653 | 0.7629 | 0.5828 | 0.7836 | **0.6426** | **0.7984** |
| | Species | 0.5620 | 0.7553 | **0.6019** | 0.7996 | 0.6013 | **0.8103** |

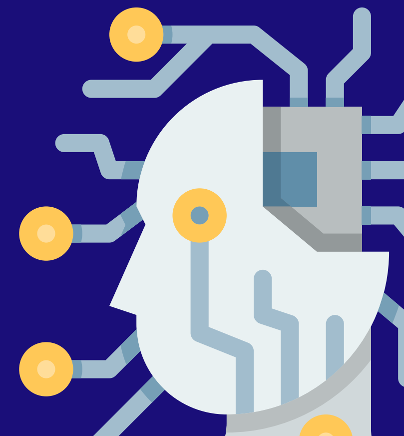
Table 3. Variants of CLIP. The significantly best results with 95% confidence are in bold.

# Resultados

## Estudio de ablación

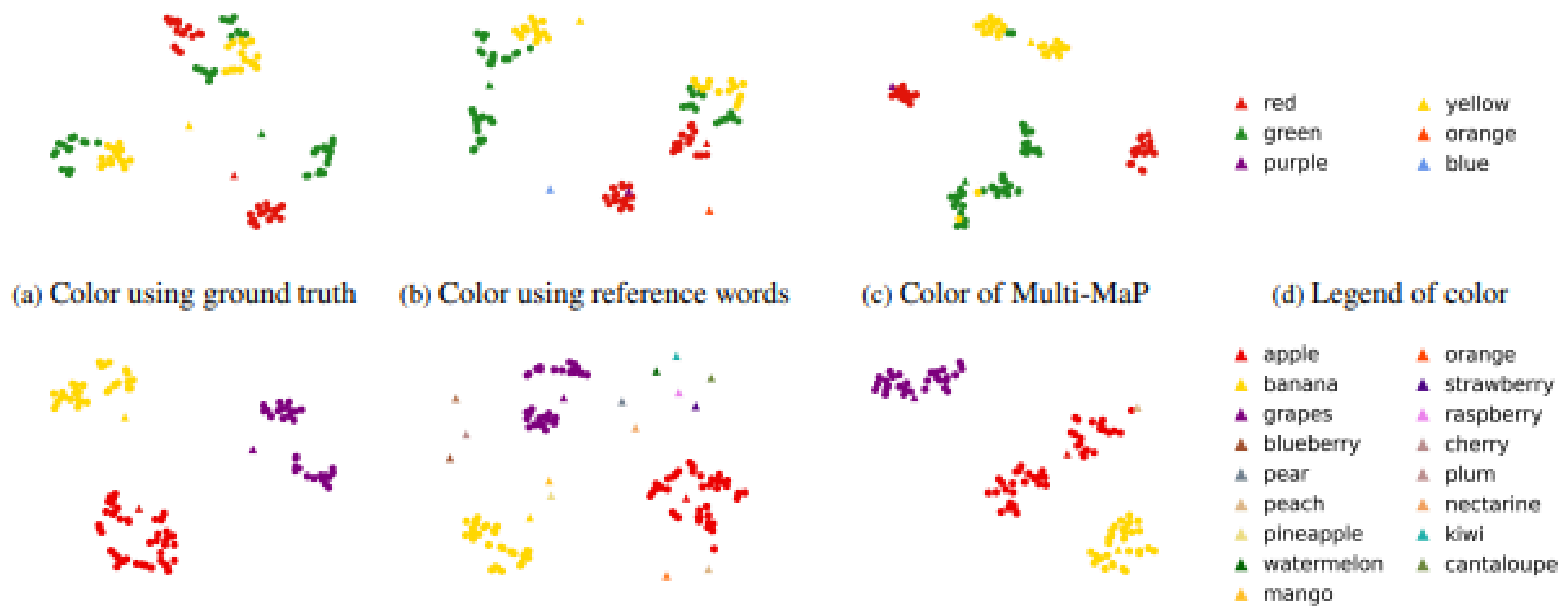
| | | Multi-MaP$_p$ | | Multi-MaP$_c$ | | Multi-MaP$_r$ | | Multi-MaP$_{cr}$ | | Multi-MaP | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Modules | Proxy Learning | ✓ | | ✓ | | ✓ | | ✓ | | ✓ | |
| | Concept Word | × | | ✓ | | × | | ✓ | | ✓ | |
| | Reference Word | × | | × | | ✓ | | ✓ | | ✓ | |
| | Contrastive Concepts | × | | × | | × | | × | | ✓ | |
| | | NMI↑ | RI↑ | NMI↑ | RI↑ | NMI↑ | RI↑ | NMI↑ | RI↑ | NMI↑ | RI↑ |
| ALOI [7] | Color | 0.9619 | 0.9826 | 1.0000 | 1.0000 | 0.9795 | 0.9869 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| | Shape | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Fruit [12] | Color | 0.7642 | 0.8439 | 0.8215 | 0.9283 | 0.8136 | 0.9073 | 0.8484 | 0.9308 | **0.8619** | **0.9526** |
| | Species | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 | 1.0000 |
| Fruit360 [35] | Color | 0.5643 | 0.7665 | 0.6217 | 0.7836 | 0.5910 | 0.7746 | 0.6089 | 0.7965 | **0.6239** | **0.8243** |
| | Species | 0.5077 | 0.7368 | 0.5137 | 0.7436 | 0.5094 | 0.7425 | 0.5199 | 0.7428 | **0.5284** | **0.7582** |
| Card [35] | Order | 0.1932 | 0.8152 | 0.3568 | 0.8472 | 0.3113 | 0.8229 | 0.3616 | 0.8094 | **0.3653** | **0.8587** |
| | Suits | 0.2375 | 0.6282 | 0.2696 | 0.6641 | 0.2498 | 0.6365 | 0.2562 | 0.6599 | **0.2734** | **0.7039** |
| CMUface [10] | Emotion | 0.1690 | 0.6170 | 0.1714 | 0.6229 | 0.1697 | 0.6360 | 0.1713 | 0.6843 | **0.1786** | **0.7105** |
| | Glass | 0.3112 | 0.6911 | 0.3269 | 0.7136 | 0.3162 | 0.6917 | 0.3370 | 0.7108 | **0.3402** | **0.7068** |
| | Identity | 0.5617 | 0.8234 | 0.6243 | 0.8359 | 0.5839 | 0.8263 | 0.6391 | 0.8946 | **0.6625** | **0.9496** |
| | Pose | 0.4361 | 0.6386 | 0.4550 | 0.6499 | 0.4381 | 0.6429 | 0.4387 | 0.6489 | **0.4693** | **0.6624** |
| Stanford cars [14] | Color | 0.5939 | 0.7835 | 0.6836 | 0.8659 | 0.6729 | 0.8638 | 0.7112 | 0.9117 | **0.7360** | **0.9193** |
| | Type | 0.5569 | 0.7996 | 0.6383 | 0.8271 | 0.6091 | 0.8046 | 0.6289 | 0.8181 | **0.6355** | **0.8399** |
| Flowers [20] | Color | 0.5783 | 0.7723 | 0.5830 | 0.7833 | 0.5987 | 0.7849 | 0.6216 | 0.7941 | **0.6426** | **0.7984** |
| | Species | 0.5704 | 0.7608 | 0.5744 | 0.7842 | 0.5723 | 0.7811 | 0.5846 | 0.7892 | **0.6013** | **0.8103** |

Table 4. Components ablation. All of our components boost performance consistently in all benchmark multi-clustering vision tasks.



# Resultados

## Visualización




(a) Color using ground truth (b) Color using reference words (c) Color of Multi-MaP (d) Legend of color

(e) Species using ground truth (f) Species using reference words (g) Species of Multi-MaP (h) Legend of species

Figure 4. Visualization of feature embeddings and related labels. The points represent the image or pseudo-word embeddings, and the triangles represent the prompt or label embeddings. Different colors represent different labels, which are indicated by the text next to the triangles.

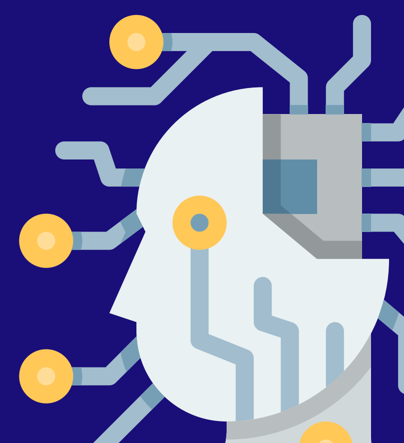
# Resultados

Desempeño destacado de Multi-MaP

- **Multi-MaP logra resultados superiores en todos los benchmarks públicos evaluados de clustering múltiple en visión por computadora.**

- **Demuestra por primera vez que CLIP puede distinguir diferentes aspectos semánticos de imágenes cuando se orienta adecuadamente por prompts específicos del usuario.**

- **La propuesta permite obtener agrupamientos personalizados, sin necesidad de etiquetas explícitas.**



# Resultados

## Limitación y futuro trabajo

- **Multi-MaP requiere que las etiquetas sean semánticamente interpretables para generar buenas referencias.**

- **Cuando las etiquetas no tienen interpretación semántica clara, Multi-MaP pierde eficacia al no poder generar referencias útiles automáticas desde GPT-4.**

# Resultados

## Limitación y futuro trabajo

- **Integración con WordNet y otros recursos externos**
- **Adaptación a dominios específicos**
- **Mejoras en selección automática de conceptos**

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