Tips to reduce the pain of image labeling

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DATAQUITAINE

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Who am I ? → Sonia Tabti

- 2024 - Present: Freelance AI specialist

AI Research
AI product Roadmap
Computer Vision
Problem solving

My clients

- 12+ years of expertise: Half corporate and half academic

PhD student → Researcher → Senior data scientist → AI team leader → Head of AI Research

That famous number you might all know about

→ 80 % of AI projects fail

→ It’s twice higher than other IT projects

Source: The Root Causes of Failure for Artificial Intelligence Projects and How They Can Succeed, J. Ryseff et al. (RAND), 2024

That famous number you might all know about

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Why is that ? Some of the main bottlenecks
• Data collection • Data labeling ← Today's focus ! • Deployment

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Outline

1. One of the main bottlenecks of AI projects
    a. Context
    b. Why is labeling so hard ?
2. Different ways to reduce the pain of image labeling
    a. Use a good interface
    b. Build a strong review methodology
    c. Some modeling strategies to ease the pain
3. Focus on Vision-Language Models to accelerate image labeling
    a. From open world models to VLMs
    b. Proposed semi-automated labeling workflow

Image labeling examples

What's labeling/annotating a data sample ?

It's the, often manual, process of assigning a label to data so that the model can be trained or evaluated on examples whose ground truth is known.

Task	Label type	Annotation process
Classification: Associate an image to a class	 - Dog ✅ - Cat	Select a class among predefined ones
Object detection: Locate objects in boxes and categorize them		Draw a bounding box (bbox) around objects of interest and select their category among a predefined list
Segmentation : Locate objects, compute their boundaries and categorize them		Draw polygons around the boundaries of objects of interest and select their category among a predefined list

Why is labeling so hard ?

- Not well understood, not anticipated
- Expansive
- Time consuming

- Limited data volume / the patterns we need to observe are rare

- Requires expertise
  - Good methodology
  - SMEs (Subject Matter Experts) must do the labeling in many cases
- Not easy to outsource
  - But if you do, write down very clear specifications

- Requires to use the right tools

Tip 1: Use a good labeling interface

For more:

- Efficient and collaborative work
- Ergonomy
- And many other features ...

Here are my two favorite open source tools to easily build labeling interfaces:

Label Studio

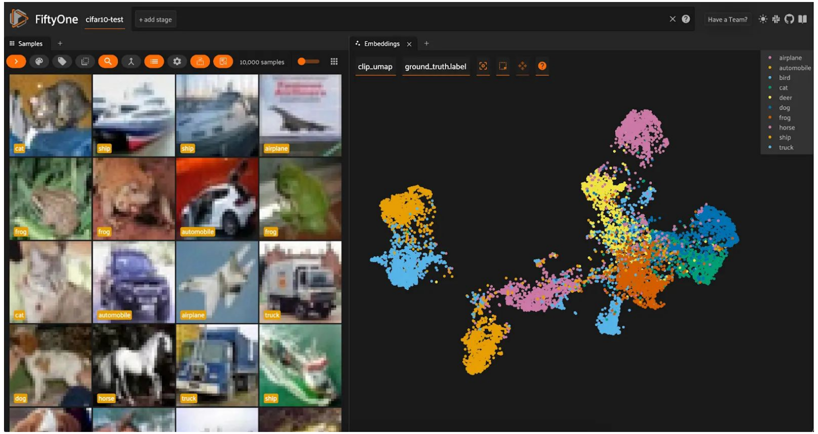
CVAT

Tip 2: Build a strong labeling review methodology

- Annotation → visual review
- Compute **stats** of the labels' distribution **regularly**
- Give **feedbacks** to the labeling team **regularly**
- Visualize the **embeddings** of the images (or bounding boxes) in 2D to spot obvious labeling mistakes
    - **How?:** You can do it yourself but I recommend to use this open-source tool:

FiftyOne

VOXEL51



Tip 3.1: modeling strategies that can help you

- Collect metadata to label the images
  - Eg: for defect detection, if reports listing the defects exist, use them
- And of course, use pretrained models - if relevant
  - Even better, check if an open-source model already exists and works for your use case
- Use data augmentation - if relevant

Tip 3.2: modeling strategies that can help you

Weakly supervised learning

→ Use less labeled data

- Unsupervised learning
  - Eg: anomaly detection
- Few shots learning
- Semi-supervised learning (SSL)

ANOMALiB

USB
Unified SSL Benchmark

Active learning

→ Improve model's performance iteratively as you label more data

→ Label in priority samples with higher uncertainty scores

Models combining text and images

They can be very helpful for:

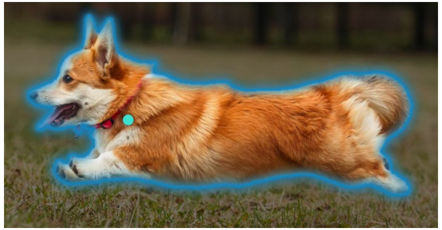
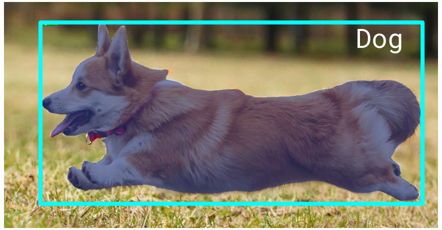
- Object detection
- Segmentation
- VQA (Visual Question Answering)
- OCR (Optical Character Recognition)
- Image captioning, …

→ You can fine tune them

→ But mostly you can use them to semi-automate data labeling and train an efficient model with this data to be deployed

We will talk more about them in the next slides …

From a foundation model to open world models 💚

Models' labeling power	SAM	Per-SAM	Grounded-SAM
Input	 Image + click or bounding-box	 Reference image + mask	 "Dog" Image + prompt
Output	 Mask of the selected object	 Mask for similar objects when applied on other images	 Bboxes and masks of the objects prompted

From a foundation model to open world models 💚

Models' labeling power

SAM → Per-SAM → Grounded-SAM

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SAM:

Image + click or bounding-box

Per-SAM:

Reference image + mask

Grounded-SAM:

"Dog"

Image + prompt

Output

SAM:

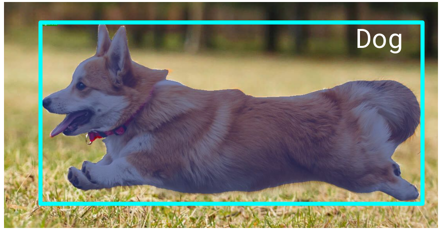
❌ Need manual input
✅ Integrated in labeling tools 🔥

object

Per-SAM:

Mask for similar objects when applied on other images

Grounded-SAM:



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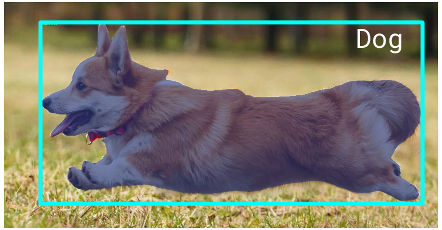
Per-SAM:

Didn't work well for my needs ❌

Mask for similar objects when applied on other images

Grounded-SAM:



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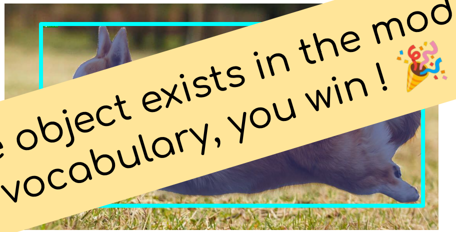
Output	 …ed object	 Mask for similar objects when applied on other images	 Bboxes and masks of the objects prompted

❌ Need manual input
✅ Integrated in labeling tools 🔥

Didn't work well for my needs ❌

If the object exists in the model's vocabulary, you win ! 🎉

From open world models to Vision Language Models

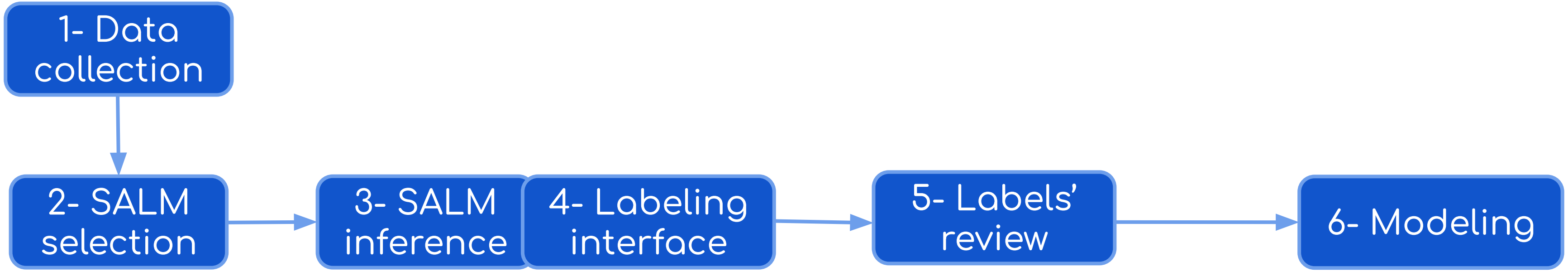
Too many **open-source** options to cite them all:

- Open world models (open-set models)
- Zero-shot models
- Large Multimodal Models
- ...

They are all great candidates to help semi-automate image labeling !

Proposed semi-automated image labeling and model training workflow

SALM = Semi-Automated Labeling Model, eg: Grounding DINO, Grounded-SAM, PaliGemma, Molmo ...



- Test different SALMs
- Test many prompts
- On many samples

Scenario 1:
- DIY inference
- Import images and metadata in the labeling interface

Scenario 2:
- Import images
- Inference using the labeling interface's backend

→ Depending on the SALM and the use case

- Visual inspection of the SALM results
- Use FiftyOne
- Bbox or mask adjustment
- Category adjustment
- Adding missed objects

Build a specialized model
- Use a relevant architecture
- ... that satisfies production constraints
- Apply transfer learning or fine tuning

Takeaways

To make image labeling more efficient:

- Check if you have metadata that can help
- Use a labeling interface and **review** the labels
- Select your modeling strategy wisely
- Take advantage of open-set models and VLMs to semi-automate the process and use this data to train a specialized model

Words by one of my clients CALi in the retail industry:

" ~38% of time was saved compared to a manual labeling process"

Thank you for your attention !

Any questions ?

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