Overton

Apple-flavored ML

2019/10/07 Nantes Machine Learning Meetup

Overview

Overview

What / When / Where

Publishing date

Early September

Conference

NeurIPS

Goal

ML software lifecycle management

Maturity

Production

Overview

Challenges to overcome

- Precise monitoring
- Complex pipelines
- Efficient feedback loop

Overview

Architectural choices

- Code-less deep learning
- Multi-task learning
- Weak supervision

Code-less deep learning

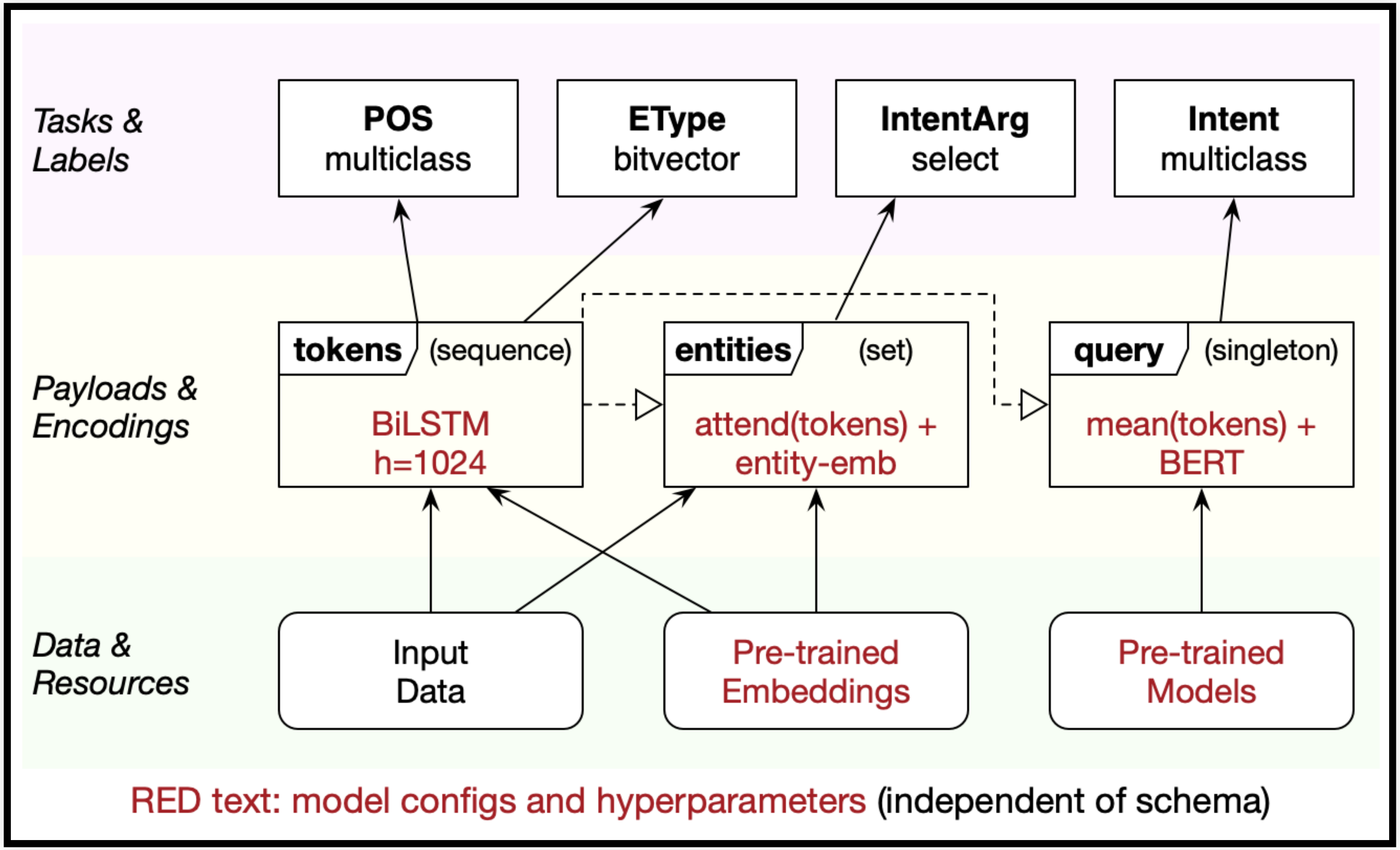
Code-less deep learning

Principles

- Models & training code = experts
- “black box” by engineers

Code-less deep learning

Modularity



Code-less deep learning

Configuration

Fine grained ML & multi-tasks

Fine grained ML & multi-tasks

Problems

- Lots of subtasks (implicit & explicit)
- Need to evaluate & monitor them
- Need to improve on them

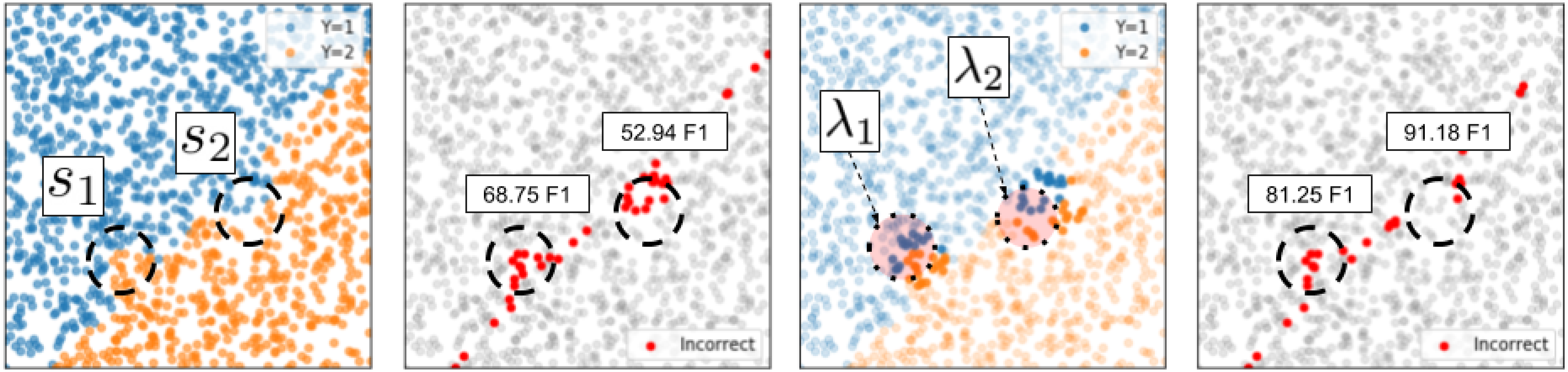
Approach

Slice-based learning

- Definition of data subsets
- Augmentation of model capacity
- Dedicated metrics

Fine grained ML & multi-tasks

Slice-based learning



(a) Synthetic data with critical slices (dashed) (b) Vanilla model errors (c) User heuristically targets slices SFs (dotted) (d) Slice-aware model errors

Fine grained ML & multi-tasks

Definition of critical data subsets

With “slice functions”:

```
def sf_bike(x):
    return "bike" in object_detector(x)

def sf_night(x):
    return avg(X.pixels.intensity) < 0.3
```

Fine grained ML & multi-tasks

Slice experts

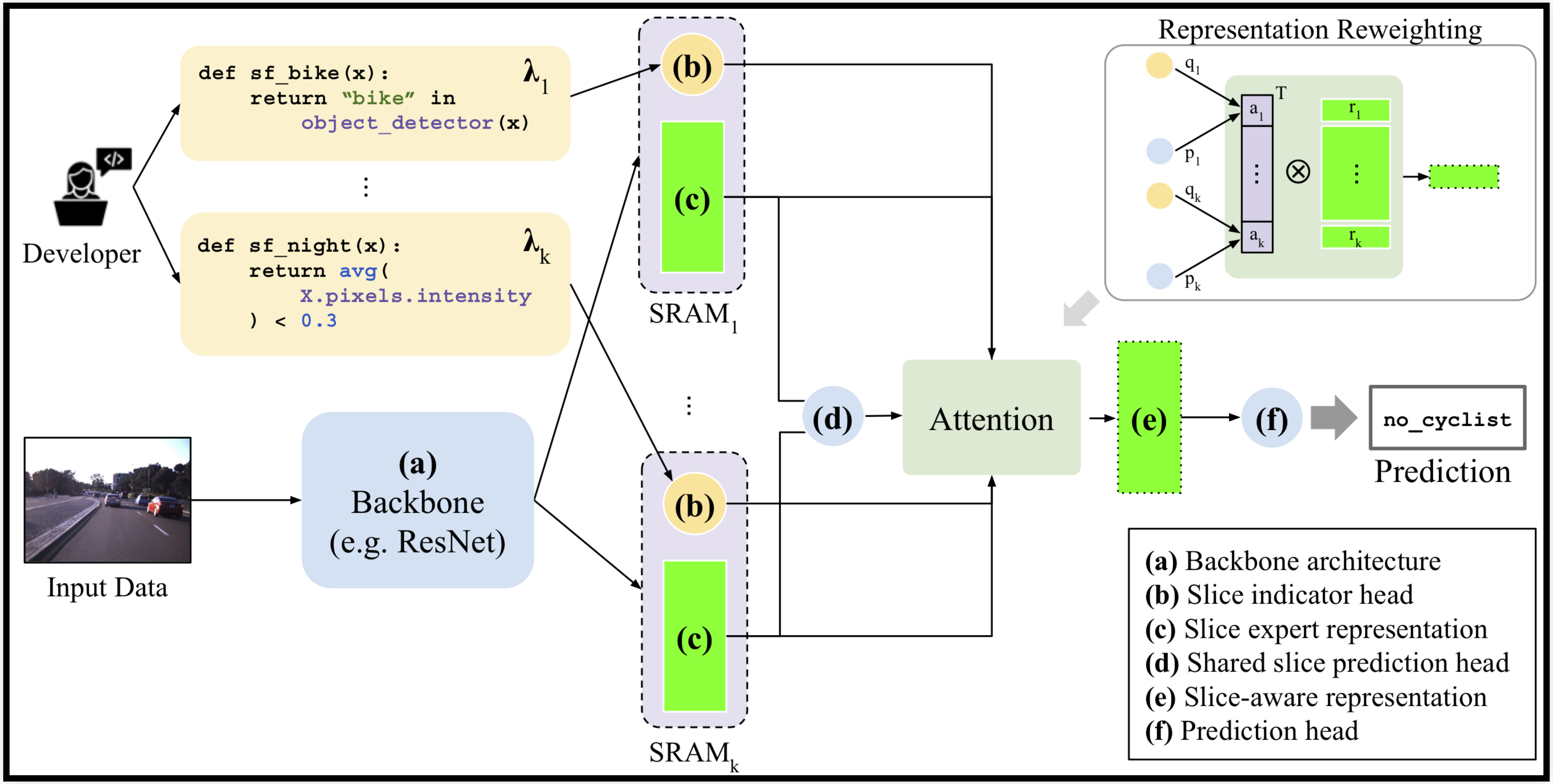
For each slice, an expert:

- should add capacity to the model
- has to know when to trigger
- has to have dedicated metrics

Hard parts

- Noise : slices are defined with heuristics
- Scale 1 : when the number of slices goes up, does the model still run fast enough?
- Scale 2 : when the number of slices goes up, is the model still good enough?

Proposed solution



Resources

- Snorkel blog “Slice-based Learning”
- NeurIPS paper “Slice-based Learning: A Programming Model for Residual Learning in Critical Data Slices”

Weak supervision

Weak supervision

Problem statement

We need data, but:

- It's expensive, not available, yadda yadda
- Especially for interesting corner cases
- It's noisy

Weak supervision

Solution

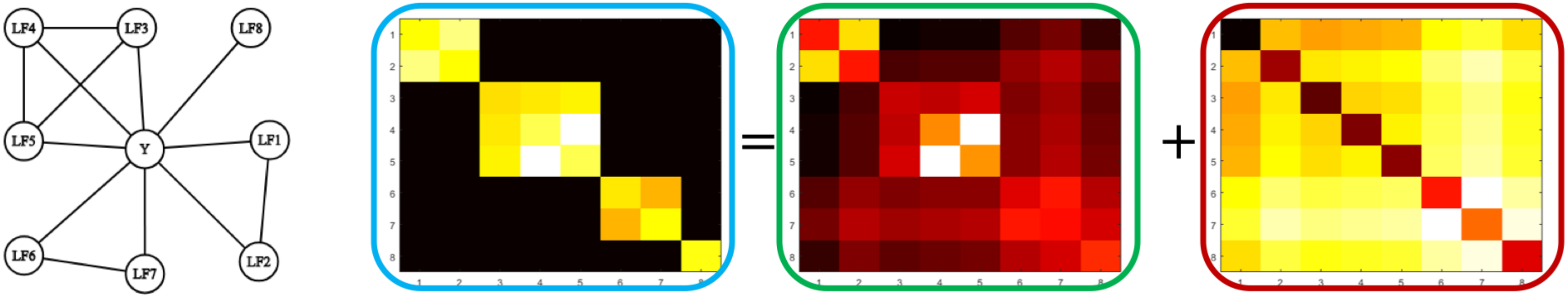
Use heuristics

```
@labeling_function()
def lf_regex_check_out(x):
    """Spam comments say 'check out my video', 'check it out', et
    return SPAM if re.search(r"check.*out", x.text, flags=re.I) e
```

Solution

Then correct the loss accounting for their correlation

$$\boxed{(\Sigma^{-1})_O} = \boxed{\Sigma_O^{-1}} + \boxed{zz^T}$$



Weak supervision

Implementation

Overton uses a modified version of the “Label Model” from Snorkel.

Resources

- Snorkel blog « Introducing the New Snorkel »
- ICML paper “Learning Dependency Structures for Weak Supervision Models”

Conclusion

- Modularity (alike AllenNLP, tensor2tensor)
- Dedicated metrics & multi-tasks
- Improvements on critical data subsets
- Artifical data with theoretical corrections

Questions / Discussion