Scallop: A Language for Neurosymbolic Programming

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Two Prevalent Paradigms of Modern Programming

Deep Learning

[System 1]

Classical Algorithms

[System 2]



Two Prevalent Paradigms of Modern Programming

Deep Learning

[System 1]

- Sub-symbolic knowledge _
- Open-domain knowledge
- Rapid reasoning _
- Handling noise and naturalness -
- In-context learning _

Classical Algorithms

[System 2]



Two Prevalent Paradigms of Modern Programming

Deep Learning

[System 1]

- Sub-symbolic knowledge
- Open-domain knowledge
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- Handling noise and naturalness
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Classical Algorithms

[System 2]

- Domain-specific knowledge
- Complex reasoning
- Interpretability
- Compositional reasoning
- Generalizability



Neurosymbolic to Combine Both Worlds ...

Deep Learning

[System 1]

Classical Algorithms

[System 2]

- Sub-symbolic knowledge
- Open-domain knowledge
- Rapid reasoning
- Handling noise and naturalness
- In-context learning

- Domain-specific knowledge
- Complex reasoning
- Interpretability
- Compositional reasoning
- Generalizability



Challenges With Combining Them



Challenges With Combining Them



- 1. Choice of Symbolic Data Representation for R
- 2. Choice of Symbolic Reasoning Language for P
- 3. Automatic and Efficient Differentiable Reasoning Engine for learning $\frac{\delta Y}{\delta R}$ under algorithmic supervision
- 4. Ability to tailor learning $\frac{\delta Y}{\delta R}$ to individual applications' characteristics
- 5. Mechanism to leverage and integrate with existing training pipelines $\frac{\delta R}{\delta \theta}$ and neural models M_{θ}



Our Approach: Scallop



- Relational Representation for R
- Datalog-based Language for P
- Provenance Semirings Framework for $\frac{\delta Y}{\delta R}$
- Integration with Pytorch for $\frac{\delta R}{\delta \theta}$ and $M_{ heta}$



A Motivating Example



State: 200x200 colored image **Action**: Up, Down, Left, Right (Environments are 5x5 grids randomized for each session)





State: 200x200 colored image Action: Up, Down, Left, Right

(Environments are 5x5 grids randomized for each session)











Step 0

Step 4

State: 200x200 colored image Action: Up, Down, Left, Right

(Environments are 5x5 grids randomized for each session)

| | Neurosymbolic (with Scallop) | DQN |
|---|--|-------|
| Success rate (reaches the goal within 50 steps) | 99.4 % | 84.9% |
| # of Training episodes (to achieve the success rate) | 50 | 50K |

(Note: this is not entirely a fair comparison since our Scallop program encodes system dynamics and human knowledge)



Differentiable Reasoning Framework











Page 17





Semantics and Provenance Framework

- The formal semantics of SclRAM is parameterized by a provenance structure inspired by the theory of Provenance Semirings [PODS'07]
- A Provenance Structure is an algebraic structure that specifies:
 - Tag Space: the space of additional information associated with each tuple
 - Operations: how tags propagate during execution

| | Ab | stra | ct Provenance | <pre>max-min-prob(mmp)</pre> |
|---------------|-----------|------|--------------------------------------|------------------------------|
| (Tag Space) | t | E | T | [0, 1] |
| (False) | 0 | € | T | 0 |
| (True) | 1 | € | T | 1 |
| (Disjunction) | \oplus | : | $T \times T \to T$ | max |
| (Conjunction) | \otimes | : | $T \times T \to T$ | min |
| (Negation) | θ | : | $T \rightarrow T$ | $\lambda p.(1-p)$ |
| (Saturation) | ⊜ | : | $T \times T \rightarrow \text{Bool}$ | == |



Provenance Framework: An Example

Scallop program SCLRAM program

rel safe_cell(x, y) = grid_cell(x, y) and not enemy(x, y) safe_cell ~ grid_cell - enemy



Untagged Semantics



Provenance Framework: An Example



Untagged Semantics

Tagged Semantics



Provenance Framework: An Example



Tagged Semantics with mmp

Untagged Semantics

Built-in Library of Provenance Structures

| Kind | Provenance | T | 0 | 1 | \oplus | 8 | θ | ⊖ | τ | ρ |
|----------------|----------------------|------------------|---|------------|---|---|-------------------------------------|-------------------------|---|--|
| Discrete | unit | {()} | 0 | 0 | $\lambda t_1, t_2.()$ | $\lambda t_1, t_2.()$ | $\lambda a.FAIL$ | == | λ <i>i</i> .() | $\lambda t.()$ |
| | bool | $\{\top, \bot\}$ | L | т | V | ^ | - | == | id | id |
| | natural | N | 0 | 1 | + | × | $\lambda n. \mathbb{1}[n > 0]$ | == | id | id |
| | max-min-prob | [0,1] | 0 | 1 | max | min | $\lambda t.1 - t$ | == | id | id |
| | add-mult-prob | [0,1] | 0 | 1 | $\lambda t_1, t_2.\operatorname{clamp}(t_1+t_2)$ | $\lambda t_1, t_2.(t_1 \cdot t_2)$ | $\lambda t.1 - t$ | λt.T | id | id |
| Drobabiliatia | nand-min-prob | [0,1] | 0 | 1 | $\lambda t_1, t_2 (1 - t_1)(1 - t_2)$ | min | $\lambda t.1 - t$ | λt.T | id | id |
| Probabilistic | nand-mult-prob | [0,1] | 0 | 1 | $\lambda t_1, t_2 (1 - t_1)(1 - t_2)$ | $\lambda t_1, t_2.t_1 \cdot t_2$ | $\lambda t.1 - t$ | $\lambda t. \top$ | id | id |
| | top-k-proofs | Φ | Ø | {Ø} | $\vee_{\mathrm{top-}k}$ | \wedge_{top-k} | ¬top-k | == | $\lambda p_i.\{\{pos(i)\}\}$ | $\lambda \varphi$.WMC(φ , Γ) |
| | sample-k-proofs | Φ | Ø | {Ø} | $\vee_{\text{sample-}k}$ | $\wedge_{\text{sample-}k}$ | ¬sample-k | == | $\lambda p_i.\{\{\operatorname{pos}(i)\}\}$ | $\lambda \varphi$.WMC(φ , Γ) |
| | diff-max-min-prob | \mathbb{D} | Ô | î | max | min | $\lambda \hat{t}.\hat{1} - \hat{t}$ | == | id | id |
| | diff-add-mult-prob | \mathbb{D} | Ô | î | $\lambda \hat{t}_1, \hat{t}_2.\mathrm{clamp}(\hat{t}_1 + \hat{t}_2)$ | $\lambda \hat{t}_1, \hat{t}_2.\hat{t}_1\cdot \hat{t}_2$ | $\lambda \hat{t}.\hat{1} - \hat{t}$ | λî.⊤ | id | id |
| Differentiable | diff-nand-min-prob | [Ô, Î] | Ô | î | $\lambda \hat{t}_1, \hat{t}_2 (\hat{1} - \hat{t}_1)(\hat{1} - \hat{t}_2)$ | min | $\lambda \hat{t}.\hat{1} - \hat{t}$ | $\lambda \hat{t}. \top$ | id | id |
| Differentiable | diffnand-mult-prob | [Ô, Î] | Ô | î | $\lambda \hat{t}_1, \hat{t}_2 (\hat{1} - \hat{t}_1)(\hat{1} - \hat{t}_2)$ | $\lambda \hat{t}_1, \hat{t}_2.\hat{t}_1\cdot \hat{t}_2$ | $\lambda \hat{t}.\hat{1} - \hat{t}$ | $\lambda \hat{t}. \top$ | id | id |
| | diff-top-k-proofs | Φ | Ø | {Ø} | $\vee_{\mathrm{top-}k}$ | \wedge_{top-k} | ¬top-k | == | $\lambda \hat{p}_i.\{\{\mathrm{pos}(i)\}\}$ | $\lambda \varphi$.WMC(φ , $\hat{\Gamma}$) |
| | diff-sample-k-proofs | Φ | Ø | {Ø} | $\vee_{\text{sample-}k}$ | $\wedge_{\text{sample-}k}$ | ¬sample-k | == | $\lambda \hat{p}_i.\{\{\mathrm{pos}(i)\}\}$ | $\lambda \varphi$.WMC($\varphi, \hat{\Gamma}$) |
| | | | | | | | | | | |



Built-in Library of Provenance Structures

| Kind | Provenance | Т | 0 | 1 | \oplus | \otimes | θ | \ominus | τ | ρ |
|---|----------------------|---|--------|-----------------|---|---|-------------------------------------|-------------------------|---|--|
| Discrete | unit bool | $\begin{array}{c} \left\{ \left(\right) \right\} \\ \left\{ \top, \bot \right\} \end{array}$ | () | () T | $\lambda t_1, t_2.()$ \vee | $\lambda t_1, t_2.()$ \wedge | $\lambda a.FAIL$ | == | λi.() id | λt.() id |
| | natural | N | 0 | 1 | + | × | $\lambda n. \mathbb{T}[n > 0]$ | == | id | id |
| Probabil Syntax and semantics of Scallop programs remains familiar to users. The provenance framework allows to customize learning performance and scalability via a rich and extensible library. $C(\varphi,\Gamma)$ | | | | | | | | | | |
| Differentiable | diffnand-mult-prob | [Ô, Î] | ô | î | $\lambda \hat{t}_1, \hat{t}_2 (\hat{1} - \hat{t}_1)(\hat{1} - \hat{t}_2)$ | $\lambda \hat{t}_1, \hat{t}_2.\hat{t}_1\cdot \hat{t}_2$ | $\lambda \hat{t}.\hat{1} - \hat{t}$ | $\lambda \hat{t}. \top$ | id | id |
| | diff-top-k-proofs | Φ | Ø | $\{\emptyset\}$ | $\vee_{\mathrm{top-}k}$ | $\wedge_{\mathrm{top-}k}$ | ¬top-k | == | $\lambda \hat{p}_i.\{\{\mathrm{pos}(i)\}\}$ | $\lambda \varphi$.WMC $(\varphi, \hat{\Gamma})$ |
| | diff-sample-k-proofs | Φ | Ø | $\{\emptyset\}$ | $\vee_{\text{sample-}k}$ | $\wedge_{\text{sample-}k}$ | ¬sample-k | == | $\lambda \hat{p}_i.\{\{\operatorname{pos}(i)\}\}$ | $\lambda \varphi. WMC(\varphi, \hat{\Gamma})$ |
| | | | | | | | | | | |



Evaluation



Benchmark Suite

Involves Computer Vision (Images & Videos)



Benchmark Suite

Involves Natural Language Processing (Natural Text)



Benchmark Suite

Requires Multi-Modal Capability (Combination of CV & NLP)



Performance: Scallop vs. Baselines



Testing Accuracy (%) on Selected Benchmark Tasks

Scallop 😴 Foundation Models

Foundation Models





Foundation Models





Context:

[Cristina] was afraid of heights just like her daughters, [**Sheila**] and [Diana]. However, [Diana]'s father, [Jonathan], loved heights and even went skydiving a few times. [**Ruth**] and her son, [Jeremy], went to the park, and had a wonderful time. [Jeremy] went to the bakery with his uncle [Jonathan] to pick up some bread for lunch.

Question:

What is the relationship between **Ruth** and **Sheila**?



Context:

[Cristina] was afraid of heights just like her daughters, [**Sheila**] and [Diana]. However, [Diana]'s father, [Jonathan], loved heights and even went skydiving a few times. [**Ruth**] and her son, [Jeremy], went to the park, and had a wonderful time. [Jeremy] went to the bakery with his uncle [Jonathan] to pick up some bread for lunch.



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```
@gpt_extract_relation(
    prompt="Please extract the kinship relationships from the context:",
    examples=[("Alice is Bob's mother", [("alice", "bob", "son"), ...]), ...])
type parse_relations(bound context: String, sub: String, obj: String, rela: String), ...
```



Context: [Cristina] was afraid of heights just like her daughters, [**Sheila**] and [Diana]. However, [Diana]'s father, [Jonathan], loved heights and even went skydiving a few times. [**Ruth**] and her son, [Jeremy], went to the park, and had a wonderful time. [Jeremy] went to the bakery with his uncle [Jonathan] to pick up some bread for lunch. What is the relationship between **Sheila** and **Ruth**?

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Context: [Cristina] was afraid of heights just like her daughters, [**Sheila**] and [Diana]. However, [Diana]'s father, [Jonathan], loved heights and even went skydiving a few times. [**Ruth**] and her son, [Jeremy], went to the park, and had a wonderful time. [Jeremy] went to the bakery with his uncle [Jonathan] to pick up some bread for lunch. What is the relationship between **Sheila** and **Ruth**?

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type parse_relations(bound context: String, sub: String, obj: String, rela: String), ...
```



Context: [Cristina] was afraid of heights just like her daughters, [**Sheila**] and [Diana]. However, [Diana]'s father, [Jonathan], loved heights and even went skydiving a few times. [**Ruth**] and her son, [Jeremy], went to the park, and had a wonderful time. [Jeremy] went to the bakery with his uncle [Jonathan] to pick up some bread for lunch. What is the relationship between **Sheila** and **Ruth**?

```
@gpt_extract_relation(
    prompt="Please extract the kinship relationships from the context:",
    examples=[("Alice is Bob's mother", [("alice", "bob", "son"), ...]), ...])
type parse_relations(bound context: String, sub: String, obj: String, rela: String), ...
```

```
rel kinship(p1,p2,rela) = context(ctx) and parse_relations(ctx,p1,p2,rela)
rel kinship(p1,p3,r3) = kinship(p1,p2,r1) and kinship(p2,p3,r2) and composition(r1,r2,r3)
rel answer(r) = question(p1,p2) and kinship(p1,p2,r)
```





Image Classification as Probabilistic Relation



@clip_classifier(["cat","dog"])
type cat_or_dog(
 bound img: Tensor,
 free label: String,



Image Classification as Probabilistic Relation



 \Box

```
@clip_classifier(["cat","dog"])
type cat_or_dog(
    bound img: Tensor,
    free label: String,
```

Page 42

Image Classification as Probabilistic Relation



| prob | id | label |
|------|----|-------|
| 0.00 | 0 | cat |
| 0.99 | 0 | dog |
| 0.98 | 1 | cat |
| 0.02 | 1 | dog |
| | | |



Image Segmentation as Probabilistic Relation

Segment Anything

Research by Meta Al

@segment_anything
type image_segment(
 bound img: Tensor,
 free id: u32,
 free segment: Tensor,



Image Segmentation as Probabilistic Relation



@segment_anything
type image_segment(
 bound img: Tensor,
 free id: u32,
 free segment: Tensor,



Image Segmentation as Probabilistic Relation



@segment_anything
type image_segment(
 bound img: Tensor,
 free id: u32,
 free segment: Tensor,





Combining Foundation Models



Question: How many green objects are there in the image?



@segment_anything
type image_segment(
 bound img: Tensor,
 free id: u32,
 free segment: Tensor)

```
@clip_classifier(["green","red",...])
type obj_color(
    bound object_segment: Tensor,
    free label: String)
```

@gpt_complete(prompt=
 "Please semantically parse the
 following question...")
type semantic_parse(
 bound question: String,
 free answer: Expr)





Evaluation



Page 48



scallop-lang.org



scallop.build/featured

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