Sequence-to-Sequence Networks Learn the Meaning of Reflexive Anaphora

CRAC 2020

Robert Frank and Jackson Petty, Yale University

Primitive Computations in Language Processing

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- Systematic Mapping:

  Kamala introduced Joe → INTRODUCED(KAMALA, JOE)

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  Kamala introduced Joe → INTRODUCED(KAMALA, JOE)

- Context-sensitive Mapping:

  Kamala introduced herself → INTRODUCED(KAMALA, KAMALA)

  Stacey introduced herself → INTRODUCED(STACEY, STACEY)

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Marcus (1998, 2001)

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    - The result:
        - Failure to predict the correct word!

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Frank, Mathis and Badecker (2013)

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- Result: No generalization for names that were not included as reflexive antecedents in the training data!

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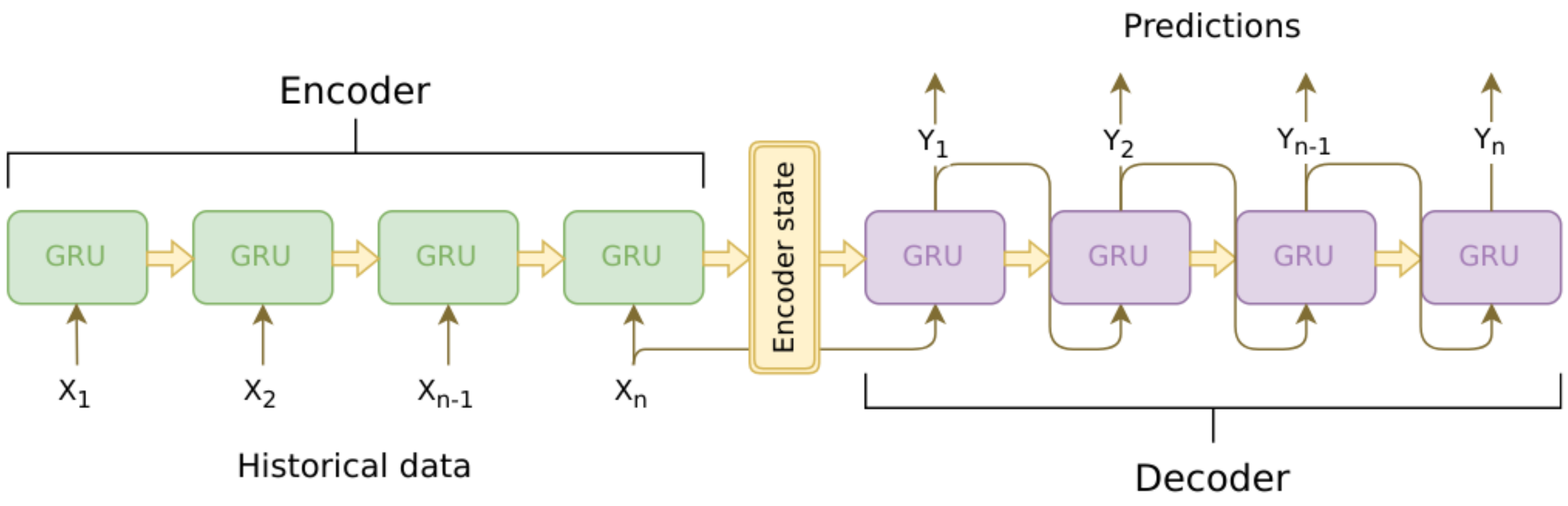
- **Sequence-to-Sequence Architectures**: more flexibility in mapping between input and output



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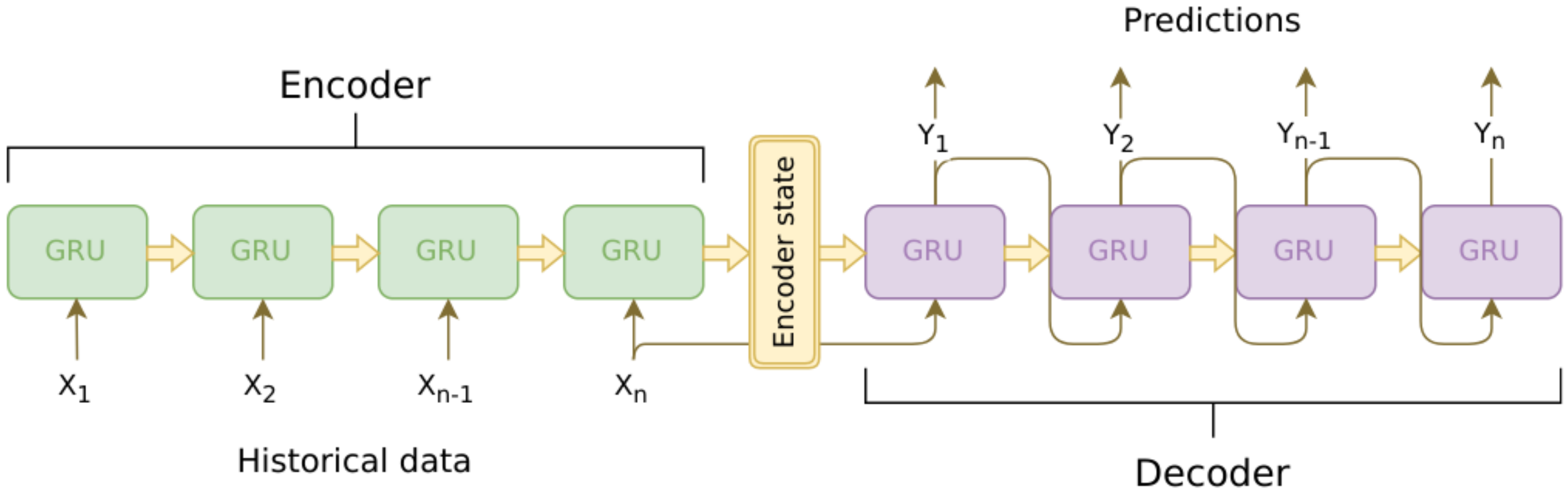

- **Attention mechanisms**: context-sensitive access to encodings

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2. What effect does lexical support have? Does the variety of antecedents for a reflexive in the training data impact the network's ability to generalize?
3. What effect does structural support have? Does the presence of an antecedent in certain structural positions during training affect how well networks learn to generalize to that antecedent?

The Dataset

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- Synthetic, pairs of simple sentences and predicate calculus expressions representing their meanings

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Bob runs → RUN(BOB)

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The Dataset

- Synthetic, pairs of simple sentences and predicate calculus expressions representing their meanings

Intransitive Sentences	**Transitive Sentences**
Alice swims → SWIM(ALICE)	John sees Claire → SEE(JOHN, CLAIRE)
Bob runs → RUN(BOB)	Alice hears Bob → HEAR(ALICE, BOB)
Claire eats → EAT(CLAIRE)	Claire knows Claire → KNOW(CLAIRE, CLAIRE)

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Transitive Sentences

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Reflexive Sentences

John sees himself → SEE(JOHN, JOHN)

Claire hears herself → SEE(CLAIRE, CLAIRE)

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Reflexive Sentences

John sees himself → SEE(JOHN, JOHN)

Claire hears herself → SEE(CLAIRE, CLAIRE)

- Intended to test whether networks can learn a context-dependent interpretation of reflexives.

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- We report ***full sentence accuracy*** for both generalization and test sets.
- For each experiment, we trained 5 randomly initialized sequence-to-sequence networks with each recurrent unit type (SRN, LSTM, GRU) with and without multiplicative attention (Luong et al., 2015).
- Trained with SGD for maximum of 100 epochs (with early stopping).

Q1: Can networks generalize reflexive meanings?

Experiment 1

Generalization

Alice *verbs* herself

Training

Claire *verbs* herself
Eliza *verbs* herself
Bob *verbs* himself
…

Bob *verbs*
Alice *verbs*
Claire *verbs*
…

Bob *verbs* Alice
Alice *verbs* Claire
Alice *verbs* Alice
…

Experiment 1

Mean test set accuracy (over random seeds)

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	No Attention	Attention

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GRU	100	100
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Q1: Can networks generalize reflexive meanings?

Experiment 2

Generalization

Alice *verbs* herself

Alice *verbs* Alice

→ VERB(ALICE, ALICE)

Training

Claire *verbs* herself
Eliza *verbs* herself
Bob *verbs* himself
…

Bob *verbs*
Alice *verbs*
Claire *verbs*
…

Bob *verbs* Alice
Alice *verbs* Claire
…

Experiment 2

Mean test set accuracy

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SRN	100	100
GRU	100	100
LSTM	100	100

Experiment 2

Mean test set accuracy

	No Attention	Attention
SRN	100	100
GRU	100	100
LSTM	100	100

Test set accuracy for **all** of our experiments is at ceiling, so we do not report it in subsequent discussion!

Experiment 2

Mean generalization accuracy

Experiment 2

Mean generalization accuracy

Experiment 2

Mean generalization accuracy

	No Attention	Attention

Experiment 2
Mean generalization accuracy

	No Attention	Attention
SRN	86	100

Experiment 2

Mean generalization accuracy

	No Attention	Attention
SRN	86	100
GRU	100	100

Experiment 2

Mean generalization accuracy

	No Attention	Attention
SRN	86	100
GRU	100	100
LSTM	100	100

Key Point, contra (Marcus 1991 and Frank et al. 2013):

Seq2Seq models ARE capable of learning an abstract reflexive meaning that generalizes to a novel antecedent!

Q2: How does lexical support affect generalization?

Experiment 3: vary number of held-out antecedents

Generalization

Alice *verbs* herself/Alice

Claire *verbs* herself/Claire

Eliza *verbs herself*/Eliza

…

Training

Bob *verbs* himself
Zelda *verbs* herself
…

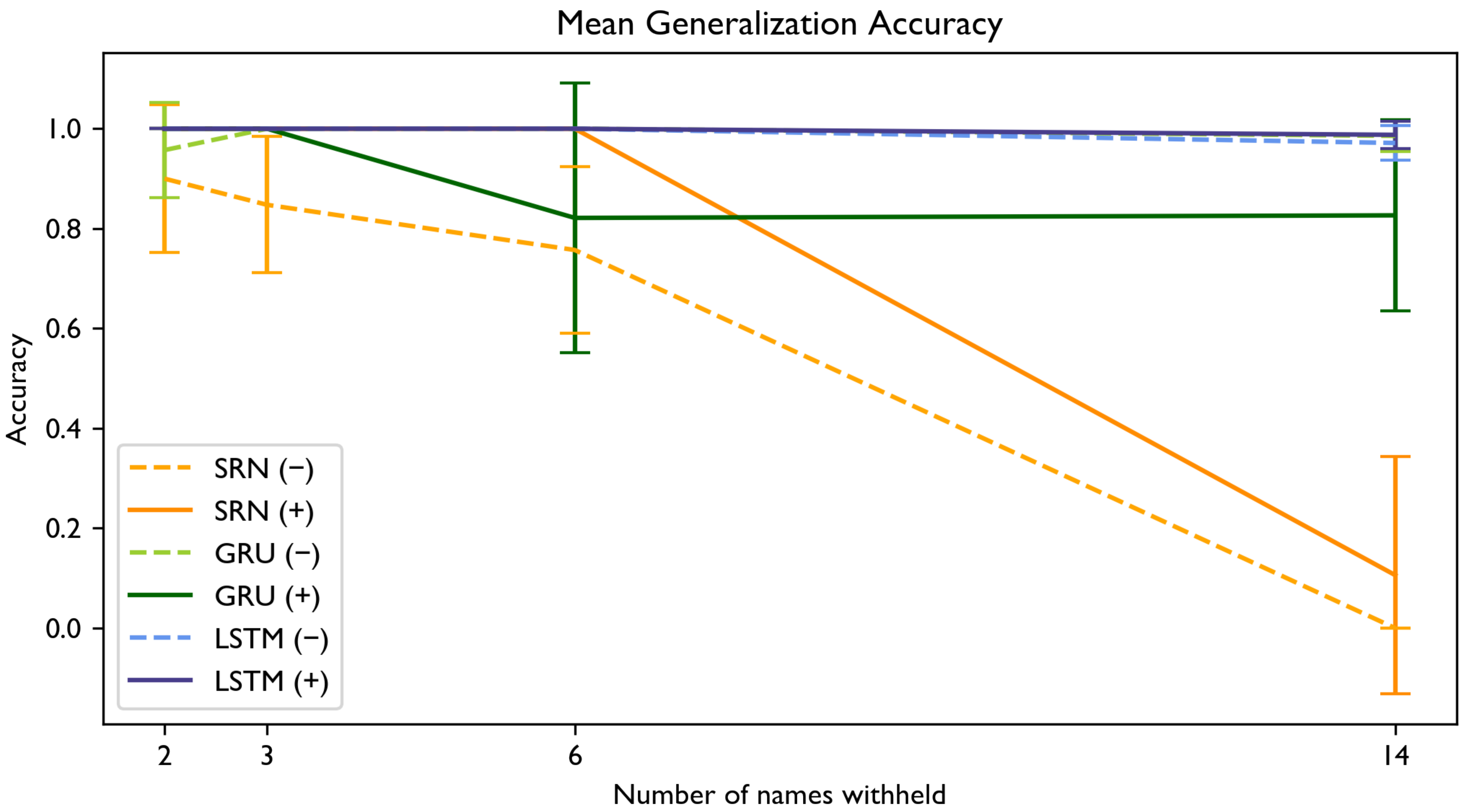
Bob *verbs*
Alice *verbs*
Claire *verbs*
…

Bob *verbs* Alice
Alice *verbs* Claire
Alice *verbs* Alice
…

Experiment 3

Generalization accuracy (on "*P verbs* herself" sentences)

- LSTMs (-) and (+) and GRUs (-) do excellently!
- GRUs (+) drop off somewhat beyond 3 antecedents withheld
- SRNs drop off significantly after 6 antecedents withheld

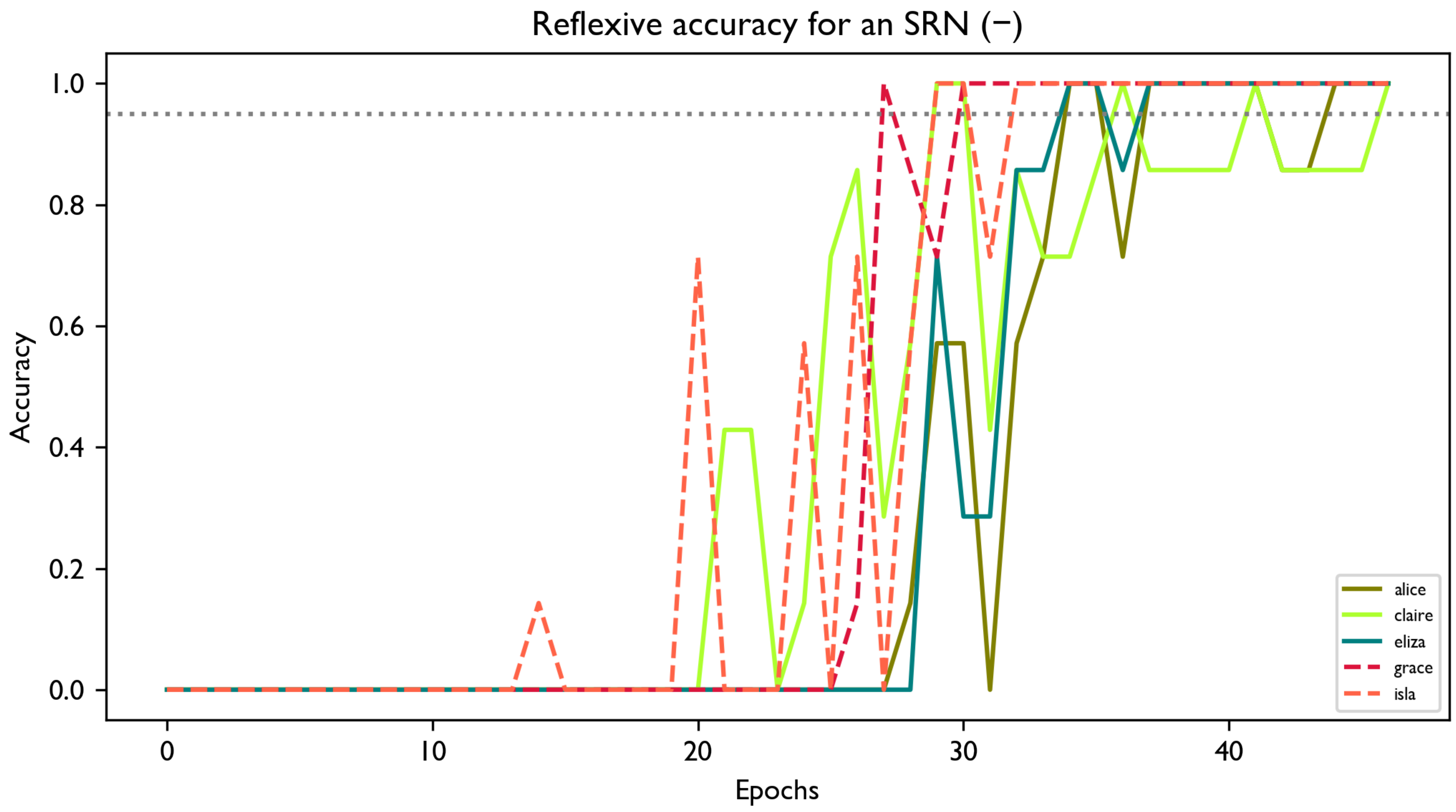


Experiment 3

Learning curve for "*P verbs* herself" sentences

- Networks learn how to interpret reflexives in a piecemeal fashion, even if they do generalize!

- In-sample antecedents (dashed lines) are typically learned before out-of sample antecedents.



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- Intransitive sentences provide an interesting point of note

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- The structure of both the form and meaning provides support
  - Impact of seeing “Alice” in subject vs object position?
  - Impact of seeing ALICE as the first vs second argument to a predicate?
- Intransitive sentences provide an interesting point of note
  - Unary predicates ⇒ ambiguity in role of single argument

Q3: How does structural support affect generalization?

Experiment 4a: Alice is no transitive subject!

Generalization

Alice *verbs* herself

Alice *verbs* Alice

Alice *verbs* Bob

Training

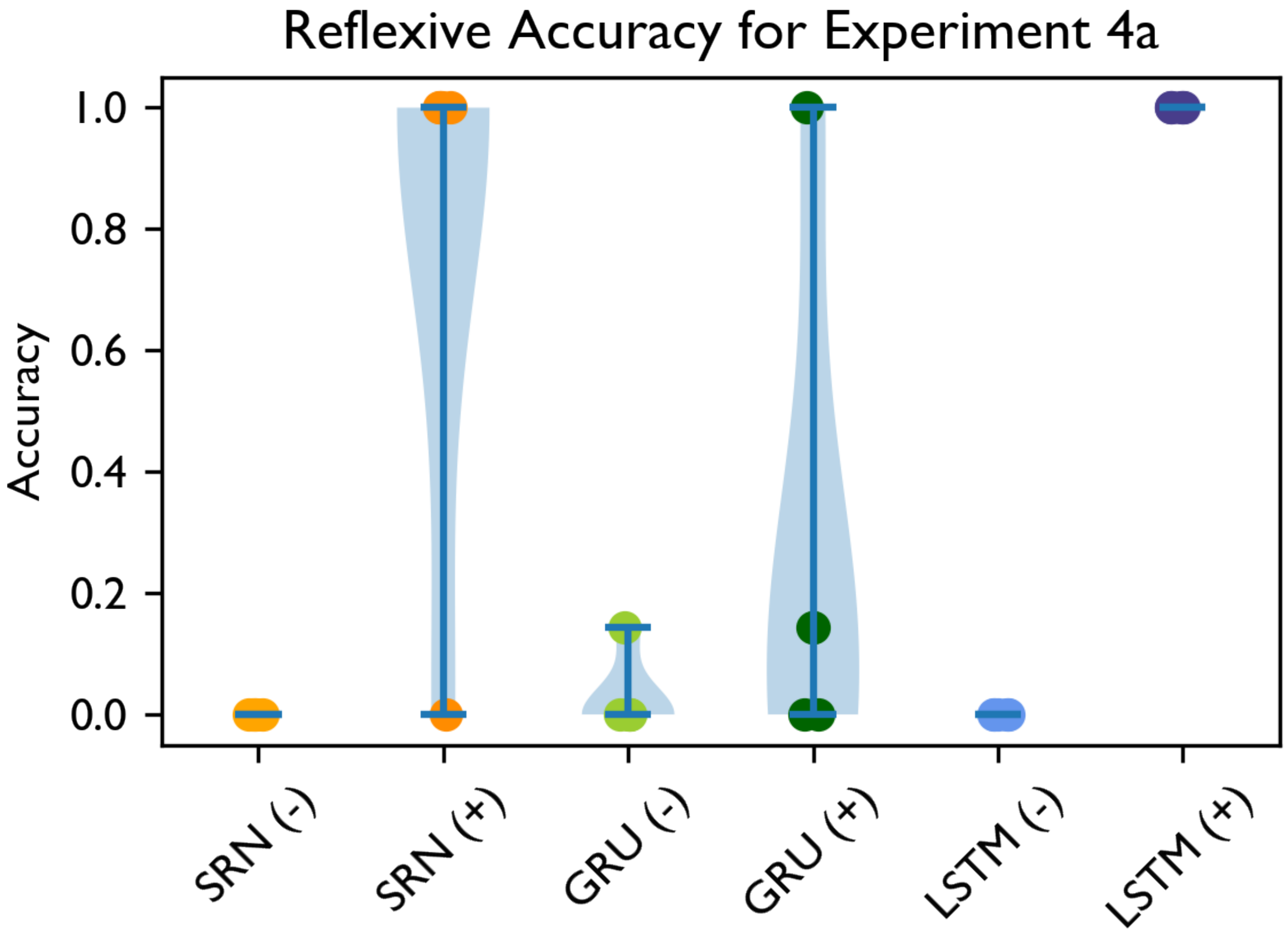
Bob *verbs* himself
Claire *verbs* herself
Daniel *verbs* himself
...

Bob *verbs*
Alice *verbs*
Claire *verbs*
...

Claire *verbs* Alice
Daniel *verbs* Bob
John *verbs* John
...

Experiment 4a

Generalization accuracy (on "Alice *verbs* herself" sentences)



SRN (-)	SRN (+)	GRU (-)	GRU (+)	LSTM (-)	LSTM (+)
0.0	**0.8**	**0.03**	**0.26**	**0.0**	**1.0**

- LSTMs (+) do excellently!
- SRNs (+) outperform GRUs (+)
- Attention definitely matters

Q3: How does structural support affect generalization?

Experiment 4b: Alice is no transitive or intransitive subject!

Generalization

Alice *verbs* herself

Alice *verbs* Alice

Alice *verbs*

Alice *verbs* Bob

Training

Bob *verbs* himself
Claire *verbs* herself
Daniel *verbs* himself
…

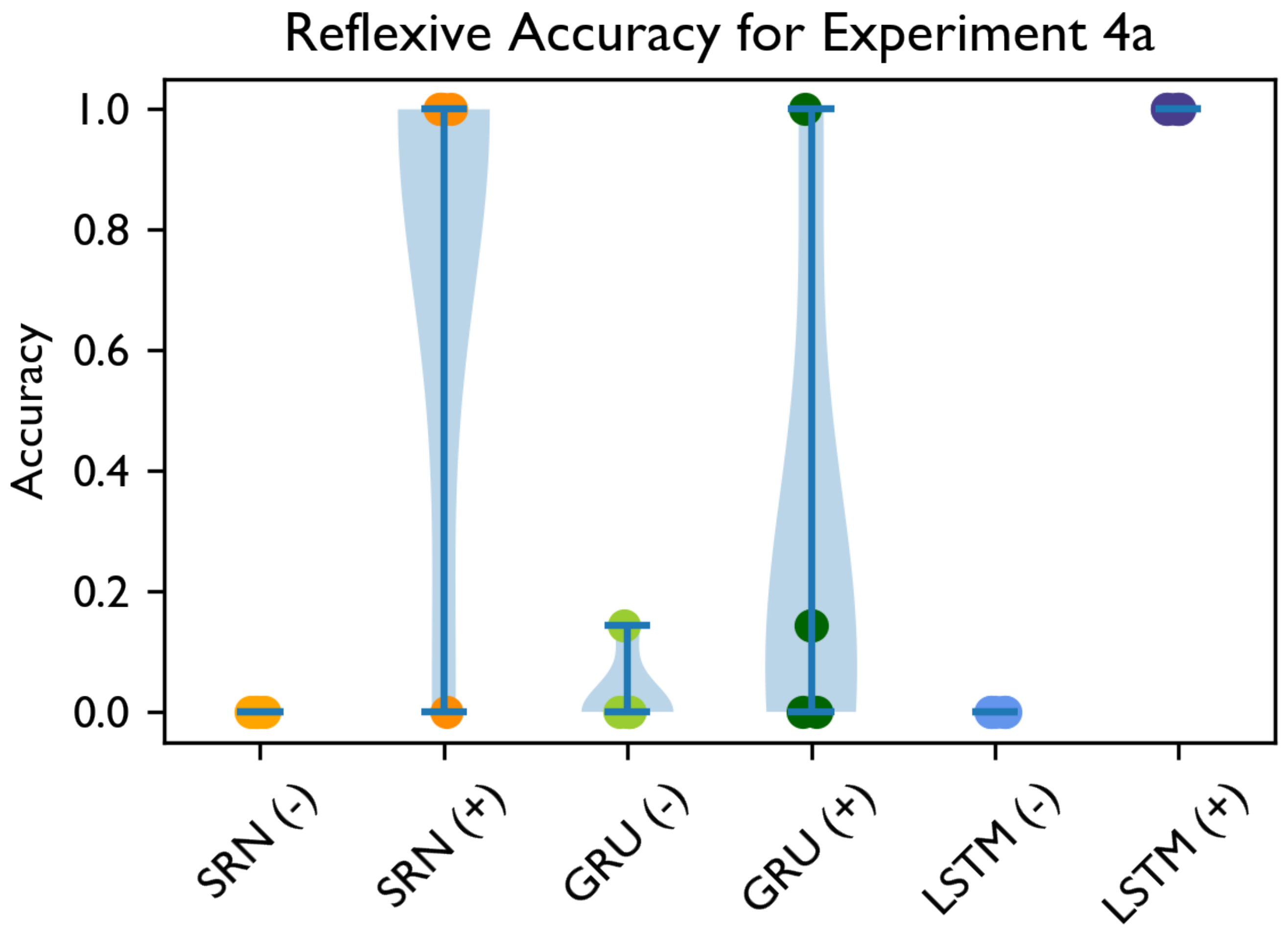
Bob *verbs*
Claire *verbs*
…

Claire *verbs* Alice
Daniel *verbs* Bob
John *verbs* John
…

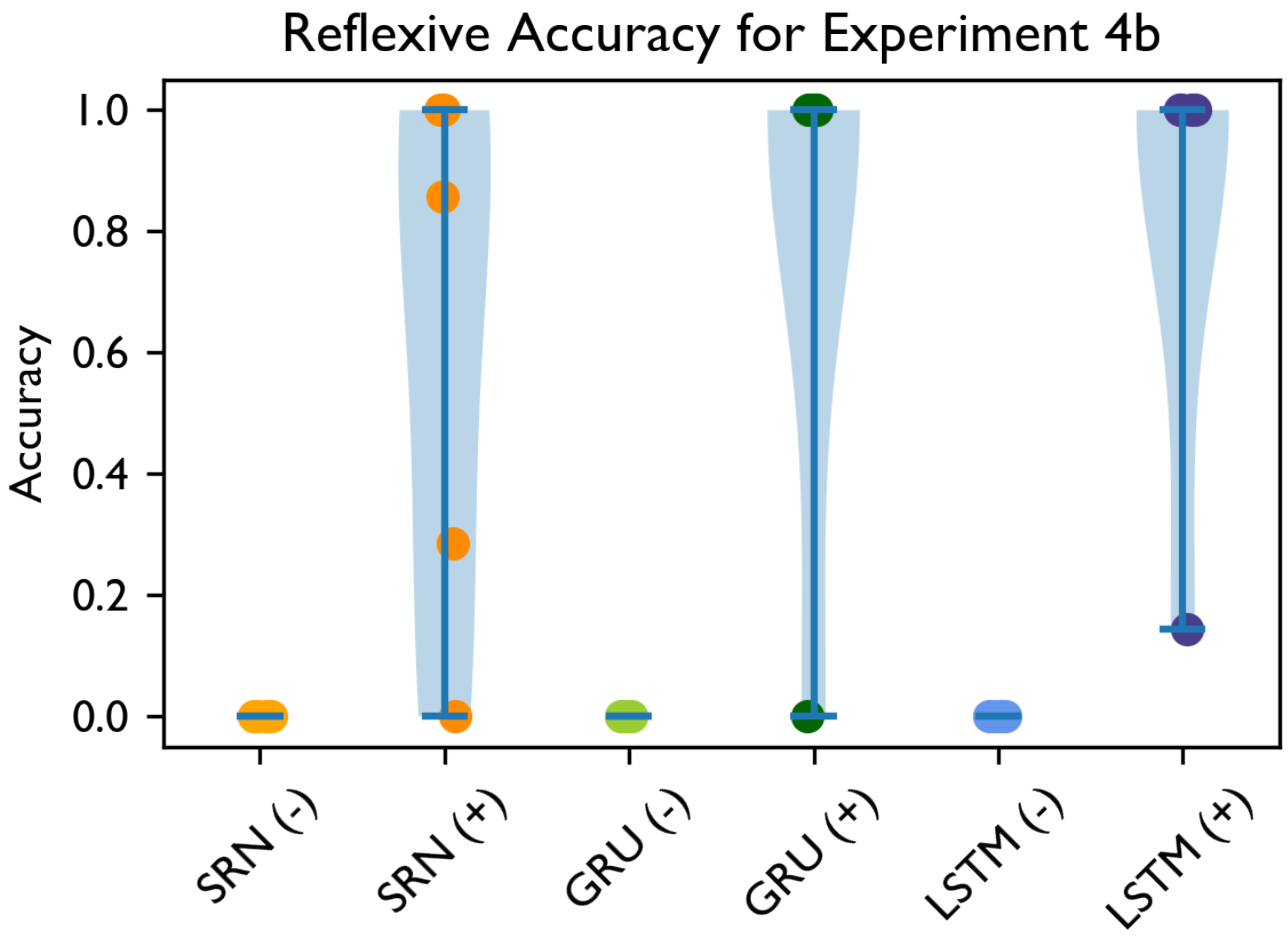
Experiment 4b

Generalization accuracy (on “Alice *verbs* herself” sentences)

- Attention still matters
- LSTM and SRN performance dropped
- **GRU performance went up**



0.0 0.8 0.03 0.26 0.0 1.0



0.0 0.63 0.0 0.8 0.0 0.83

Q3: How does structural support affect generalization?

Experiment 5a: Alice is no object!

Generalization

Alice *verbs* herself

Alice *verbs* Alice

Bob *verbs* Alice

Training

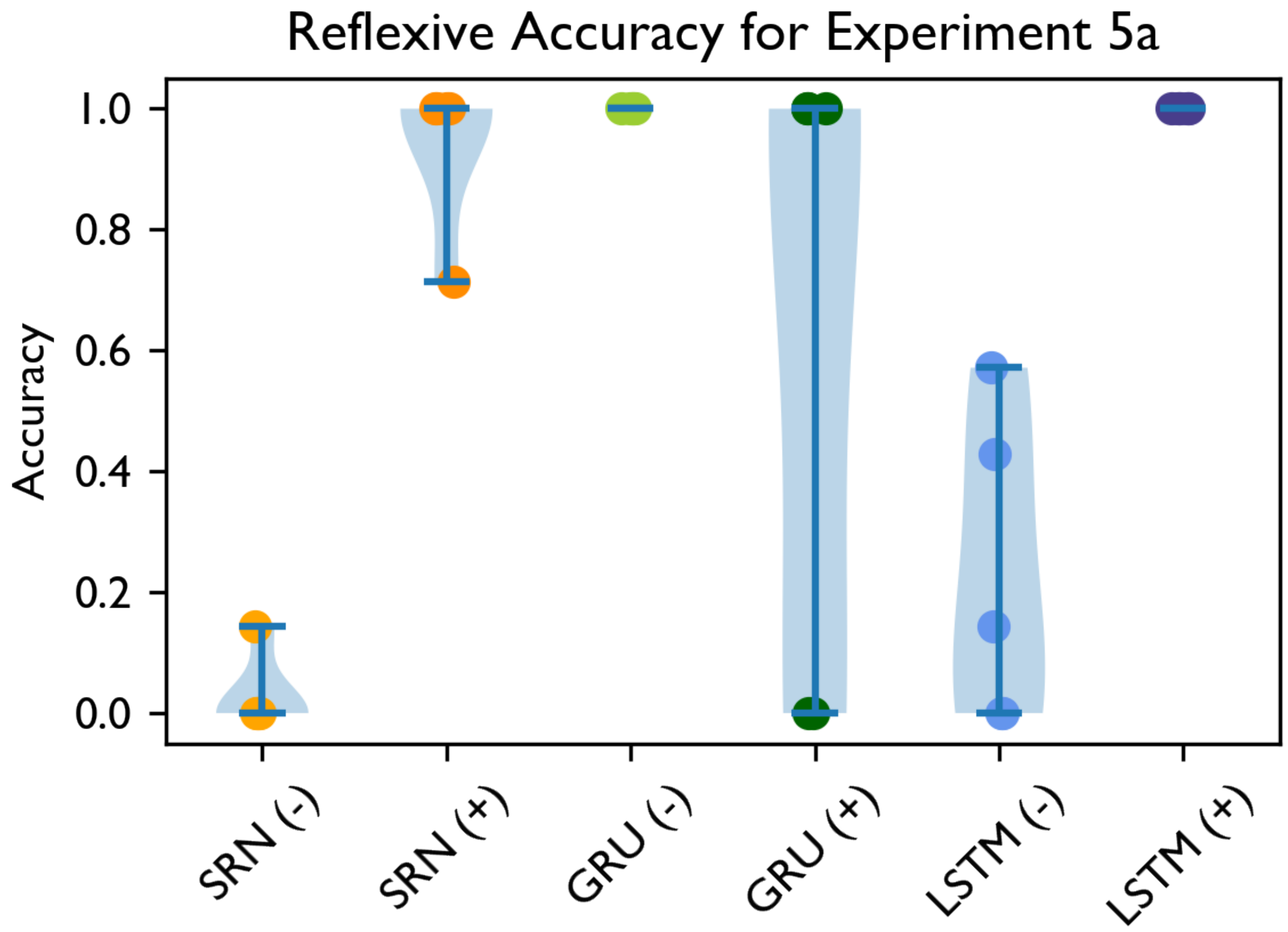
Bob *verbs* himself
Claire *verbs* herself
Daniel *verbs* himself
…

Bob *verbs*
Alice *verbs*
Claire *verbs*
…

Alice *verbs* Claire
Daniel *verbs* Bob
John *verbs* John
…

Experiment 5a

Generalization accuracy (on “Alice *verbs* herself” sentences)



0.03 0.94 0.98 0.60 0.23 1.0

- LSTMs (+) do excellently (again)!
- SRNs (+) outperform GRUs (+) (again)!
- GRUs (-) perform excellently!?

Q3: How does structural support affect generalization?

Experiment 5b: Alice is no object (or intransitive subject)!

Generalization

Alice *verbs* herself

Alice *verbs* Alice

Alice *verbs*

Bob *verbs* Alice

Training

Bob *verbs* himself
Claire *verbs* herself
Daniel *verbs* himself
…

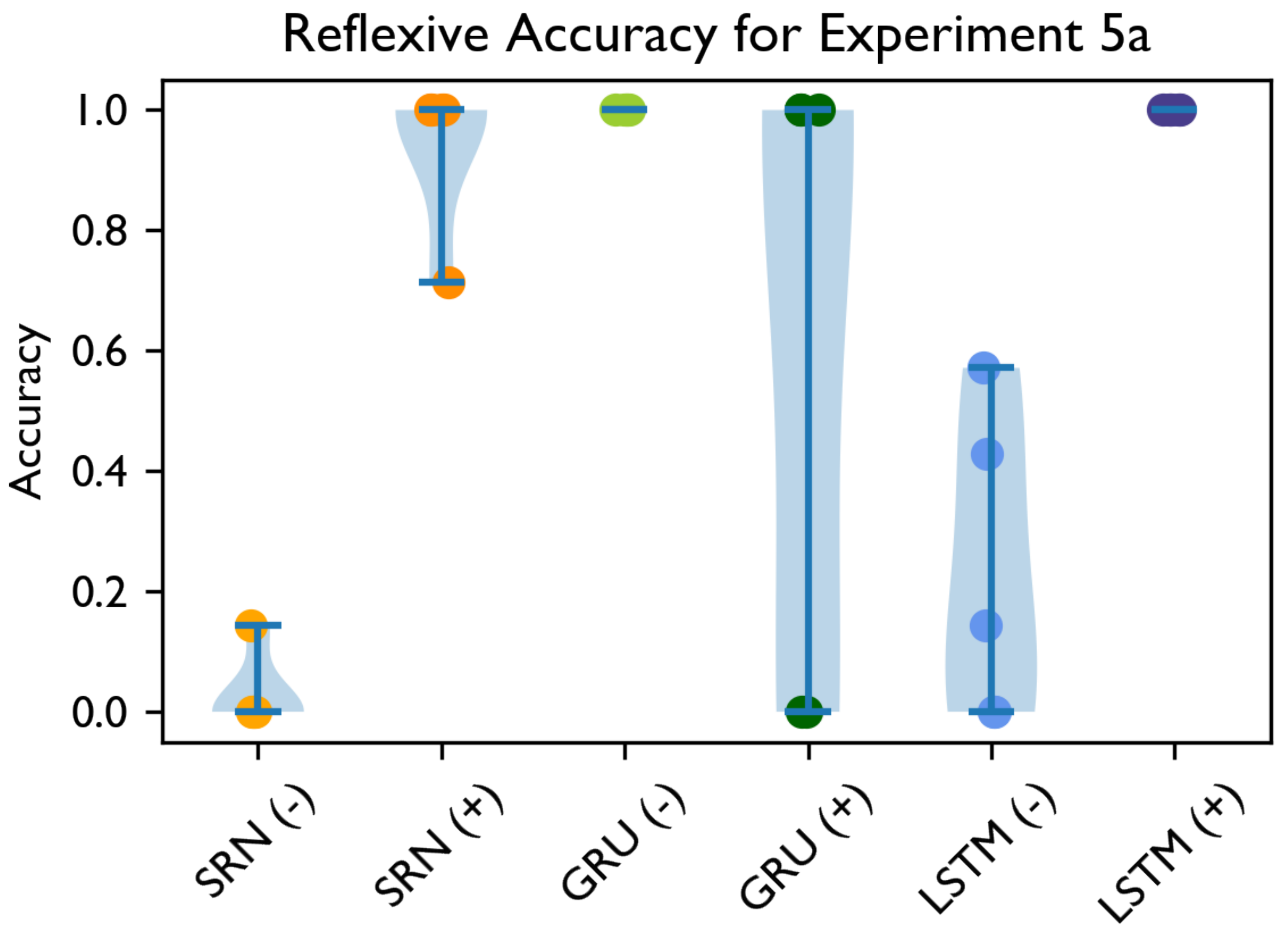
Bob *verbs*
Claire *verbs*
…

Alice *verbs* Claire
Daniel *verbs* Bob
John *verbs* John
…

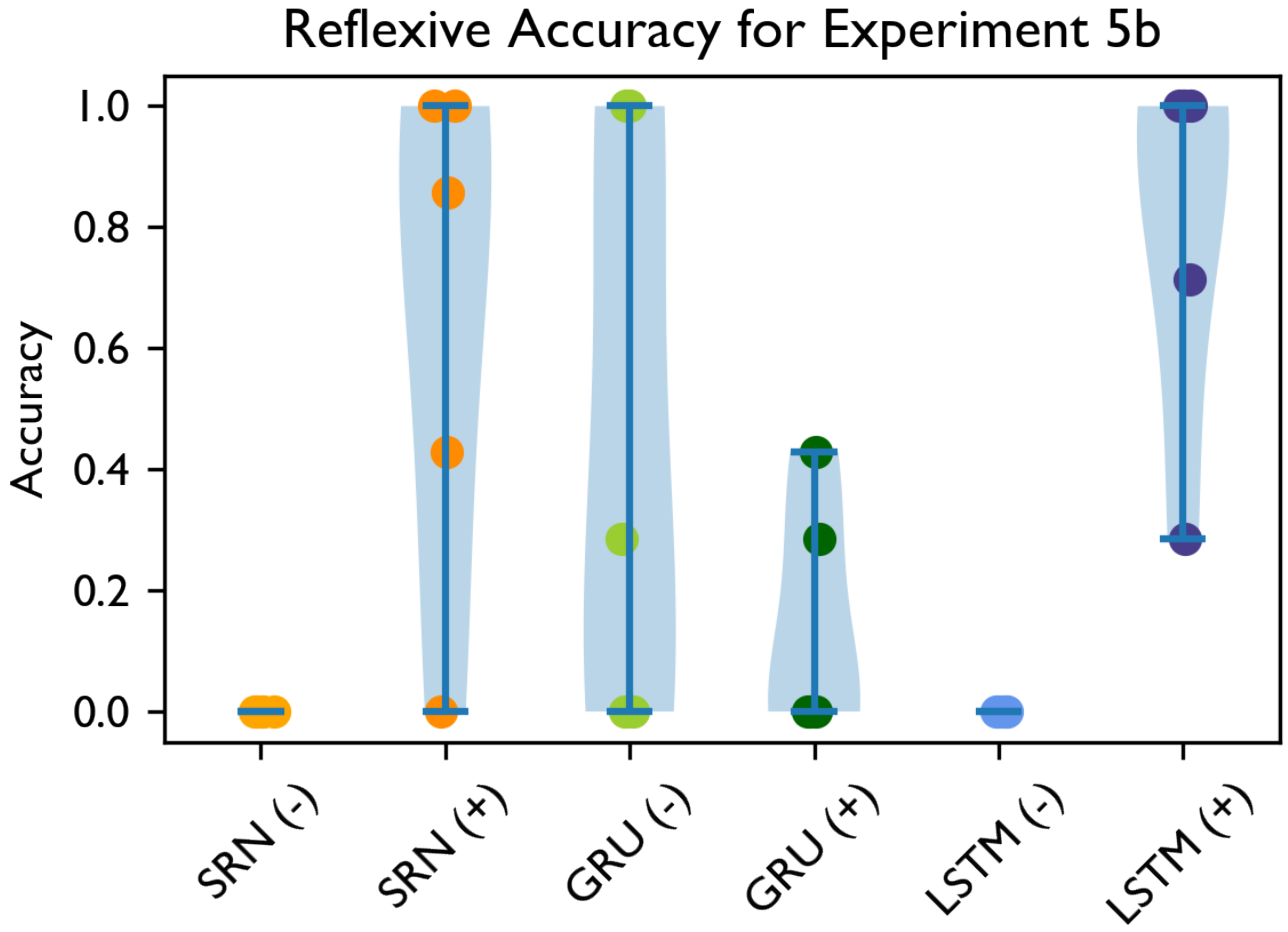
Experiment 5b

Generalization accuracy (on “Alice *verbs* herself” sentences)

- Performance degrades overall



0.03 0.94 0.98 0.60 0.23 1.0



0.0 0.65 0.45 0.14 0.00 0.80

Questions with which we began...

1. Are modern neural networks capable of algebraic generalization in reflexive anaphora? Can they learn to interpret a reflexive with a novel antecedent?

   Yes! Seq2Seq architectures with even the simplest recurrent unit (SRNs) and no attention can do it!

2. What effect does lexical support have? Does the variety of antecedents for a reflexive in the training data impact the network's ability to generalize?

   Generalization depends on the number of antecedents presented during training, though this varies by architecture. LSTMs and GRUs generalize in the presence of limited lexical support.

3. What effect does structural support have? Does the presence of an antecedent in certain structural positions affect how well networks learn to generalize to that antecedent?

   Presence of the antecedent as a subject or object in non-reflexive sentences in training does affect generalization.

Open questions

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- Structural dependence of anaphora

    The student near the teacher sees herself → SEE(STUDENT,STUDENT)

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- Structural dependence of anaphora

    The student near the teacher sees herself → SEE(STUDENT,STUDENT)

- Relation to systematicity and SCAN (and proposed solutions)

    jump twice → JUMP JUMP

Thank you for watching

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