

Masked Hard Attention Transformers Recognize Exactly the Star-Free Languages

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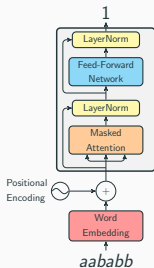
Background

Over inputs of unbounded length,
what problems can (and can't)
transformers solve?

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what problems can (and can't)
transformers solve?

and how can we prove it?

Expressivity: Transformer Encoders and Formal Models



$$\forall i. Q_a(i)$$
$$\forall i. (Q_a(i) \rightarrow \exists j. (i < j \wedge Q_b(j)))$$

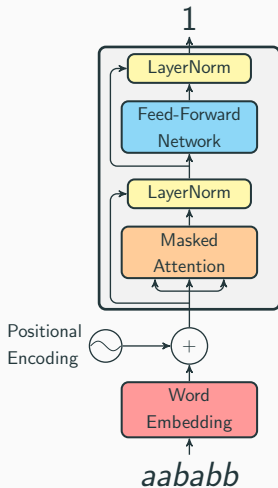
etc.

What formal languages
are recognized by
transformer encoders?

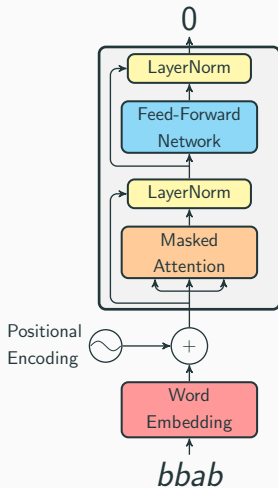
What formal languages are
defined by logical formulas?

Masked Hard Attention Transformers

Transformer Encoders



Transformer Encoders



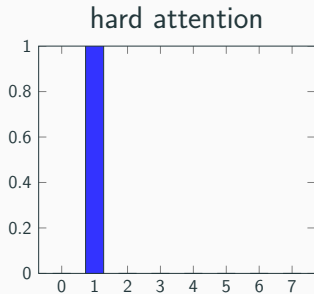
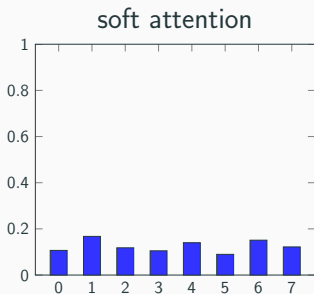
Strict Future Masking

Each position can only attend to positions strictly to the left



Leftmost/Rightmost Unique Hard Attention

Focus all attention on a single position - find maximum score and break ties to the left/right



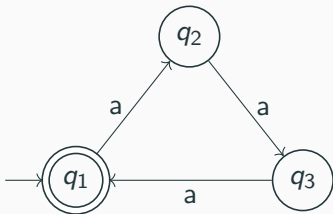
Main Result



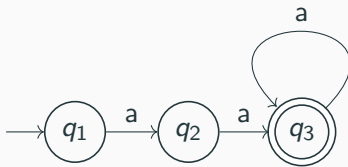
Star-Free Languages

What are Star-Free Languages?

Periodic (regular)



Aperiodic (star-free)



Examples of Star-Free Languages

Dyck-1 of Depth 2 (matched parentheses 2 deep)

$(ab)^*$ (repeated ab 's)

$\Sigma^* aa \Sigma^*$ (strings that contain substring aa)

$\Sigma^* ab (\Sigma \setminus \{a\})^* ab$ (building block of induction heads)

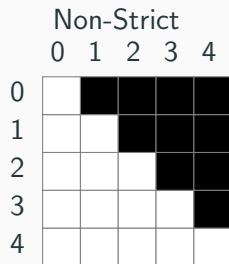
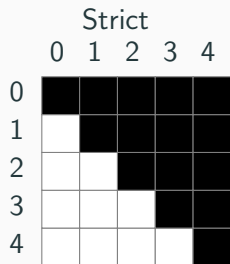
Main Result



Corollaries

How does using strict vs non-strict masking affect expressive power?

Non-Strictness



Strict masking is more expressive

Theorem

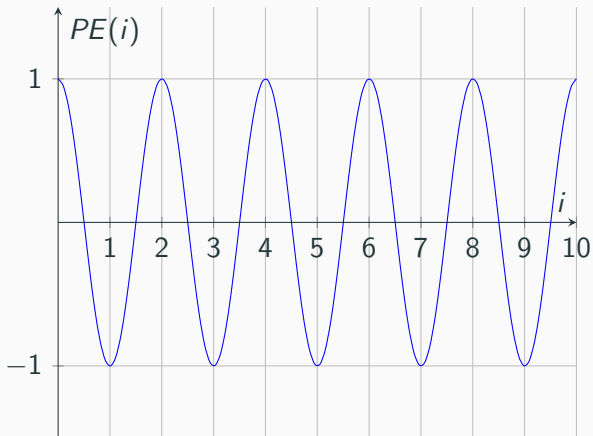
Masked hard-attention transformers with only non-strict masking recognize exactly the stutter-invariant star-free languages.

For instance

- $(ab)^*$ is not stutter invariant
- $(a^*b^*)^*$ is stutter invariant

How do positional embeddings affect expressive power?

Positional Embeddings



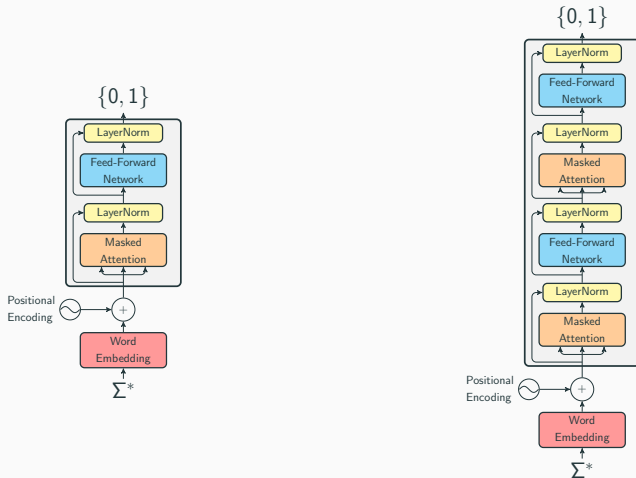
Using sinusoidal position embeddings
is more expressive

Theorem

Masked hard-attention transformers with rational sinusoidal positional embeddings recognize exactly the regular languages in AC^0

How does adding more layers affect expressive power?

Transformer Depth



Adding more layers is more expressive

Theorem

Masked hard-attention transformers with $k + 1$ layers are strictly more expressive than masked hard-attention transformers with k layers

It requires $k + 1$ layers to recognize the language STAIR_{k+1}

Parting Notes

Limitations

- Hard attention results may not apply to softmax attention
- We don't consider autoregressive language modeling
- No claims on empirical learnability

Formal language theory can quite effectively explain the computational behavior of masked-hard attention transformers